Rents from Tagged Energy Technology Subsidies

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Abstract

This paper empirically studies the role of observable firm and technology characteristics in reducing rents obtained from a Dutch adoption program aimed at the adoption of innovative energy technologies. Such characteristics can be used as instruments by the regulator to reduce rents. Exploiting variation across firms and technologies in our paneldata of this program, we demonstrate that both firm and technology characteristics can be exploited to improve subsidy effectiveness. In fact, the probability that a firm is free riding on the program is directly correlated with the payback period of the technology and the level of the investment. In addition, we find that firms using an explicit investment criterion are less likely to reap substantial rents. As conditioning characteristics we find that larger firms as well as horticulture firms are more likely to use an explicit investment criterion. We conclude that tagging of subsidies may substantially reduce rents.

Keywords: Rent extraction; Tagging; Tax expenditure programs; Technology adoption subsidies; Investment decisions; Bivariate probit model.

JEL Codes: D21; H25; H32; O33; Q48.

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1 Introduction

In this paper we empirically study the relationship between the design of energy technology adoption subsidies and their effectiveness. The aim of regulators to shift firms' investment decisions towards technologies with low energy use is bristling with pitfalls. According to standard principal agent theory such subsidies are likely to suffer from rent extraction due to either adverse selection or moral hazard because the regulatory agency can only imperfectly observe which (type of) agent would change his behavior due to the subsidy. This argument has been exploited, for instance, by Wirl in a series of papers (e.g. Wirl, 1995, 1999 and 2000). He argues that the subsidy contracts usually applied in practice, such as those under the US Demand Side Management (DSM) program, would reach only agents that are already inclined to invest (adverse selection) or induce firms to conceal their type (moral hazard).

In practice, however, regulators might constrain eligibility of subsidies to certain (observable) conditions and, accordingly, design so called 'tagged' incentive schemes (Akerlof, 1978). The basic idea behind such a tagged incentive scheme is to exploit observable information on the firm's investment decision. Although the regulator cannot direclty observe the firm's type, he might use other information that is observable *and* correlated with the probability of the firm being a free-rider. Such information could then be used as conditioning characteristics in the design of the subsidy scheme.[1] In the context of energy subsidy technologies, for instance, the regulator might use information implicitly revealed by the choice of technology. To illustrate, suppose a firm invests in a heat pump and applies for a subsidy. The information revealed by this particular investment is that the firm has a demand for heat. As a consequence the regulator knows that the alternative investment for this firm would have been a less efficient heat pump (with a certain probability). The firm cannot credibly mimic to be of any other type. By using characteristics

[1] Note that Wirl (1999, p.26) assumes that the demand for more energy efficient appliances would increase with consumers' type as characterized by their discount rates or pay back periods (PBP). Therefore the incentive compatible contract he proposes is *increasing* in the energy efficiency of the appliances. This would induce consumers with high PBP to reveal their type. However, we find no empirical evidence for this fundamental assumption in our sample. Instead we find that characteristics of *both* the decisionmaking process within the firm *and* the subsidized technologies themselves play a key role in designing effective subsidy mechanisms. To avoid confusion we consider the 'critical payback period' to be a characteristic of the firm, whereas the payback period of the investment is a characteristic of the technology. For example, a firm with a critical payback period of 10 years will not invest in a technology having a payback period of 20 years.

of alternative technologies available on the market - such as their energy efficiency and market shares - the regulator may prescreen options before deciding whether or not to subsidize this particular investment. Furthermore, the regulator may observe that investment decisions of particular firms are correlated with certain observable characteristics of the firm, like size and sector, and exploit this information when designing its subsidy scheme.

To the best of our knowledge no study currently exists on the the use of conditioning characteristics by regulators in designing tagged incentive schemes to reduce rent extraction by firms. In particular, we know of no empirical analysis that has explicitly studied the role of such characteristics in relation to firms' decision making. This paper aims to fill this gap in the literature. The advantages of 'tagging' are documented in the context of welfare programs (e.g., Parsons, 1996). More recently Zivin and Zilberman (2002) have extended the idea to health economics, but this literature has not focused on decision making by firms. Also previous empirical work on DSM programs has focused on household decision making and did not account for eligibility issues (e.g., Malm, 1996; Haugland, 1996). The only paper that we know of evaluating the firm's decisonmaking process in the context of a subsidy program is De Canio and Watkins' (1998) study of firms' participation decisions in the voluntary Green Lights program of the US Environmental Protection Agency. Green Lights membership is positively associated with good environmental performance by firms and with sectoral and regional characteristics suggesting the importance of informational diffusion. Technology adoption programs clearly differ from the Green Light program, however, because they directly affect (separate) investment decisions. Our conjecture in this paper is that firm heterogeneity, i.e. the probability that a firm is a free rider, is likely to be correlated with certain observable information like certain technology and firm characteristics. Examples are the payback period of the technology in which the firm invests, the level of the investment made, the size of the firm, and the sector in which it operates. The first two are examples of technology characteristics, the third and the fourth are examples of firm characteristics that might reveal how firms evaluate their investment decisions.[2] Whenever rent extraction by firms differs considerably along the dimensions of these conditioning characteristics, the regulator might use this information

[2]Indeed, firms typically vary as to how they make their investment decisions (Graham and Harvey, 2001). Large firms rely heavily on present value techniques and the capital asset pricing model (CAPM), while small firms are more likely to use the payback criterion (PBP) if they use capital budgeting methods at all.

in order to optimize its incentive scheme.

Our study is based on two 'tagged' subsidy programs introduced in the Netherlands in 1997. Both schemes aim to increase penetration of innovative energy-saving technologies for both (small) for-profit and not-for-profit firms using (partial) compensation of the investment cost differential which is made conditional on technologies that qualify for the subsidy. Technologies that qualify are prescreened based on market share (should be small) and energy saving potential (should be large). The set of technologies eligible for subsidy is updated once a year. To evaluate these programs we collected data on 862 investment decisions by both profit and not-for profit firms involved in both programs. This results in a dataset covering 20 different types of subsidized energy saving technologies across 57 sectors (classified at a 4-digit level). From the actual decisions made by the firms we not only know the (economic and physical) characteristics of the subsidized technologies and the actual investment criterion used by the firms, but also whether - according to its own judgement - the firm's investment decision has changed because of the subsidy. We use this information to determine which observable characteristics of the subsidized technology or the firm might be used by the regulator to predict the probability that any particular firm with observable characteristics is a free rider. This information may then be used to minimize rent extraction by firms.[3]

Our results are based on a bivariate probit model and confirm, first of all, the importance of firm characteristics in the distribution of rents. In particular, we find that *the framing of investment decisions by firms* is strongly correlated with the probability of being a free rider. In addition, we find that the way in which firms frame their investment decision is correlated with observable characteristics like the size of the firm and the sector in which they are active. In our particular sample of firms about half claims *not* to use any capital budgeting technique to evaluate investment decisions.[4] The other half computes economic consequences of an investment project explicitly, but mainly through the simplest of capital budgeting techniques, i.e. payback period (PBP). We find that larger firms are more likely to use the payback period as a capital budgeting technique and that the use of the payback period differs extensively between sectors. Agricultural and transport firms are much less likely to use a capital budgeting technique compared to horticulture firms.

[3]We cannot address the effect of the conditioning characteristics on agents outside our sample, i.e. agents that have adopted these technologies without subsidy or not at all. From an experimental analysis of subsidized adoption decisions by managers in firms we find evidence, however, that our result might be extrapolated (see Aalbers et al., 2009).

[4]This effect is uncorrelated with for-profit firms or not-for profit firms in our sample.

In addition we find clear evidence of the importance of technology characteristics in the distribution of rents. Firms investing in technologies with high payback periods are less likely to be a free rider compared to firms investing in technologies with low payback periods. Also, firms investing in expensive technologies are less likely to be a free-rider compared to firms investing in cheap technologies. This confirms our idea that the regulator may use both technology and firm characteristics as a screening device for reducing rent extraction.

This paper proceeds as follows. Section 2 provides background information on the two Dutch subsidy programs in the Netherlands that form the basis for our analysis. Section 3 presents our empirical model, while Section 4 presents the results. We conclude in Section 5.

2 Background and Data

This section provides background information on the characteristics of the tagged adoption programs that we evaluate. The technology adoption incentive schemes that we study in detail are two subsidy programs introduced in 1997 by the Dutch government, the so called EIA (Energy Investment Credit) targeted at (small) for-profit firms and the EINP (Energy Investment subsidy Non-Profit sector) targeted at (small) not-for-profit firms. The subsidies aim to stimulate the adoption of technologies with desirable characteristics from a social perspective, such as reductions of CO_2 emissions. Examples of such technologies are wind turbines, high-efficiency glass and insulation, which save on energy or fossil fuel use.

Usually these environmentally more favorable options are more expensive and the subsidies reduce the financial gap in private costs between the alternatives. Under both schemes firms investing in energy-saving technologies receive a partial compensation for their investment costs. EIA compensation is a tax deduction, and the EINP offers a subsidy as a percentage of the amount invested. The advantage for firms varies with the level of investment and does so at a decreasing rate.[5] Under the EIA, the net advantage obtained by firms depends on the tax rate and varies between 14 and 33%.[6] For-profit firms may carry-over any net-operating losses to

[5] In 1997 the tax deduction granted under the EIA varied between 52% for investments up to € 29,000 and 40% for investments larger than € 224,000. The investment figures are updated on a yearly basis with the consumer price index. As of 2002 the tax deduction is 55% irrespective of the size of the investment.

[6] For the time period covered by our sample, Dutch tax rates are 35% for limited liability companies and vary between 33% and 60% for (partnership) firms. The net advantage for for-

the three past and seven subsequent years, which in most instances will allow them to cash the tax deduction up to any present value considerations. Under the EINP, the not-for-profit firms may obtain a subsidy between 14.5 and 18.5% of the amount invested. Typically, the number of EINP-applications has been about 10% of the number of EIA-applications.[7]

The critical feature of both incentive schemes for our analysis is the so-called Energy-List. This list determines up front which technologies and firms are eligible for compensation and which are not. Both the overall number and the type of technologies on the 'Energy-List' vary from year to year. For instance, the overall number of technologies has varied between 80 and 110 between 1997 and 2005, and around 30% of the technologies are renewed each year by the enforcement agency Senter.[8] Criteria for inclusion of technologies are that: (i) the use of the technology should result in a substantial reduction in energy use or emissions; and (ii) the technology is not common. Technologies on the list are carefully scrutinized each year and technologies that no longer meet these criteria are removed. The Energy-List typically differs between the two subsidy schemes, as not-for-profit firms typically invest in different types of technologies than for-profit firms. Only a small number of technologies, like insulation, energy-efficient lightning systems and frequency converters, appear (or have appeared) on both lists.

[Insert Table 1 around here]

Table 1 presents information from the regulatory agency Senter on the number and size of the applications for the EIA between 1997 and 2003.[9] Since 1997 the number of applications has grown steadily until in September 2002 the possibilities for application for an EIA subsidy were temporarily ceased because of overdrafting.[10] In order to prevent future overdrafting, the criteria for eligibility have become stricter as of 2003. Over the years, around 90% of the EIA-applications have been submitted by small companies (viz. companies with a maximum of 100 employees). The share of investments by small companies has risen from 32% in 1998 to 87% in 2003. Furthermore, every application for the tax credit or the subsidy has been checked by the enforcement agency Senter in order to prevent fraudulent claims. These

profit firms is given by the tax credit times the tax rate(s).

[7] The EINP was terminated in 2001.

[8] The current Energy-List can be downloaded from www.senternovem.nl (in Dutch).

[9] Unfortunately comparable information is not available for the EINP.

[10] This was due to a small number of extremely large applications which would have nearly doubled the 2002 expenditures under the program.

checks may include company visits in order to check whether the technology filed has indeed been installed. On average, Senter approves 80-85% of the amount claimed. Moreover, a small number of all applications is withdrawn voluntarily and represents around 3-6% of the amount claimed.

Clearly the Dutch regulator exploits the Energy List as an incentive device by screening technologies before they are made eligible for subsidization. At the same time firms screen the technologies on this list using financial investment criteria. Rents typically accrue if firms apply for subsidization, but the subsidy has no effect on their adoption decision. To illustrate, suppose that firms rank potential investments in energy technologies according to their Net Present Value (NPV). Standard economic theory suggests that any rational firm should invest in the most profitable technology, provided that its NPV is larger than zero. This should be the case irrespective of the type of firm that is involved and whether it belongs to different risk classes or not (so even if, for example, the critical payback period applied to evaluate the profitability of the technology differs across firms). Accordingly, a technology for which the price is lowered by providing a subsidy should be adopted more often or earlier in time.[11]

To empirically study the role of conditioning characteristics, like the Energy List, in determining the rent-incentive trade-off, we evaluate investment decisions by individual firms involved in these subsidy programs using both register and survey data. We compiled a micro panel dataset with information from the enforcement agency Senter which was supplemented with field data obtained from a survey among firms who have been granted the subsidy between 1997 and 1999.[12] Using the Senter database we selected twenty technologies on the basis of the following criteria. First, each of the selected technologies had to have been continuously on the Energy-List between 1997 and 1999 in order to avoid strategic behavior by firms. Second, technologies for which the number of successful applications submitted was smaller than twenty, were excluded from our sample. Finally, we selected the top twenty of technologies in terms of total investment cost, defined as the sum of the individual investment costs. Ten of the twenty technologies belonged to the EIA scheme only, seven to the EINP scheme only, and three to both the EIA and EINP scheme. Most of the selected technologies are rather common, like Combined Heat Power (CHP)

[11] Even though option value theory has stressed the importance of uncertainty with respect to future costs and benefits for the adoption decision (Pindyck, 1991), there is no additional effect on the relative attractiveness of investment options related to subsidization.

[12] The complete (translated) questionnaire is available upon request from the authors.

installations, high-efficiency boilers and insulation.

Based on the selection procedure described in the previous section, we obtained 4,967 and 513 records from Senter for the EIA and EINP, respectively. After corrections for partnership firms as well as for applicants applying for more than one technology, we sent our questionnaire to 2,353 EIA-applicants and all 513 EINP applicants.[13] From the response of 776 surveys (32.9%) for the EIA and 237 surveys (46.2%) for the EINP, 673 respectively 189 surveys proved to be useful. Response rates were representative across the technologies (with only some minor under-representation of insulation and energy-conserving cooling and freezing equipment, type B). The Senter database in combination with the questionnaire allowed us to construct a very detailed representative panel of firms with information on not only the type of technology in which they invested and for which they received subsidy, but also how they make, both in general and in this specific case, investment decisions. The Senter database contains information on the type of technology, the level of investment, the year the application was submitted and the sector in which the firm in question operates. Senter also provided us with so-called reference-technologies, i.e. technologies that a firm would have invested in, had it not invested in the subsidized technology. Senter determined these reference-technologies, their costs and energy use on the basis of a 1999 survey and expert opinion. The reference-technology is characterized by 'no investment' for 12 out of the 20 investigated technologies.

We used these reference-technologies together with information on sectoral energy prices supplied by the CPB Netherlands Bureau for Economic Policy Analysis to compute firm-specific payback periods both in years and in euro/TJ.[14] Sectoral energy prices are likely to be a good proxy for energy prices paid by individual firms in our sample for two reasons.[15] First, the Dutch gas market was not liberalized prior to 2001. Second, although the Dutch electricity market was liberalized in July 1999 for large users, this has affected only an estimated 3.1% of energy prices paid in our

[13] For partnership firms the schemes require that each partner separately files an application for a percentage equal to his or her partnership. We consider these partners as a homogeneous agent for the purpose of making their investment decision. This reduces the EIA database from 14,837 to 4,967 observations. Note that under Dutch law partnership firms cannot be not-for-profit firms.

[14] Payback periods (measured in years) were calculated by dividing the additional investment of the energy-saving technology by its yearly energy savings in euros. Payback periods in euro/TJ (also called quasi payback periods) were calculated by dividing the additional investment of the energy saving technology by the yearly energy saving in TJ.

[15] Our approach of using energy savings *relative* to a reference investment is less sensitive to variations in energy prices (and thus monetary benefits) over the technology horizon.

sample. Table 2 provides details on the characteristics for the technologies analyzed in our sample, such as investment cost of the technology and its reference option, the percentage subsidy obtained (relative to the additional investment cost)[16], *PBP* and number of observations. Note that all these estimates are firm specific.

[Insert Table 2 around here]

The questionnaire yields information reported by firms about their background characteristics, like turnover and legal form. Furthermore, it provides detailed information on their investment decision making process, i.e. the financial method they used for evaluating this specific investment project (internal rate-of-return, payback period, or none) and the critical values used in this evaluation (minimal internal rate-of-return or critical payback period). To evaluate whether firms' decisions have been affected by the subsidy scheme, we asked them whether the investment would also have been made without delay, would the firm not have been eligible for compensation. Firms also reported on the level of other subsidies, if any, obtained for the technology in question, the information set of the firm just prior to the time of investment (when did they learn about the technology and the subsidy scheme), and the prime motive for investing in the technology. To signal both relevance and importance of our research, the questionnaire was accompanied by a letter signed by the minister that explicitly told respondents that their answers would be used by the government to improve subsidy schemes in the future which may explain our high response rates. Note, finally, that even though we hypothesize that no rents accrue if a subsidy induces a firm to choose a technology that would otherwise not have been selected, our main interest is in whether and how these stated responses vary systematically across firms that have applied for these ('tagged') subsidies.[17] Indeed, our aim is to illuminate the role of the conditioning characteristics of a given 'tagged' subsidy program and not to establish the *absolute* level of rent extraction by firms. More general inferences on the potential efficiency gains of tagging in terms of the rent-incentive trade-off would require comparison of these programs with groups not subject to the 'tagged' subsidy.

[16] Note that only for a relatively small subsample the value of the tax deduction variable may differ under the EIA. By far the largest subset of firms in our sample faces an income (capital) tax rate equal to 0.35.

[17] This leaves two possibilities in the absence of the scheme, i.e. (i) the firms would have cancelled the investment, or (ii) they would have postponed the investment. In the estimation we make no distinction between postponement and cancellation. Results are not affected.

[Insert Table 3 around here]

Sample statistics for the data set are provided in Table 3. Investment costs of our technology sample are higher than the average for all EIA applications (see Table 1) and range from € 56,600 to € 6,872,500. Mean investment costs of reference technologies, i.e. for 310 investment decisions (36%), is lower than expected and varies between € 2,400 and € 5,842,000. Furthermore, the mean value of the annual energy-cost savings measured in monetary terms is € 27,400 (or 16% of the mean investment cost in our sample), which is considerable. Note also that the variation in payback periods is substantial. Whereas the average payback period in our sample is 9.8 years, for some technologies it is smaller than one year, whereas for others it is more than 40 years.[18]

3 Estimation Model

Before presenting our estimation model, it is useful to discuss more indepth the responses that we have obtained on the investment decision-making process of the firms within our sample. Like Graham and Harvey (2001) we find that large variation exists as to how firms frame their investment decisions. On the question which method the firm used to evaluate this specific investment, 41% indicates that they use (critical) payback, 4% uses the internal rate-of-return,[19] while 43% claims not to use any explicit method for the evaluation of this investment.[20] Particularly interesting is the large number of firms that claims *not* to use *any* kind of (simple) financial evaluation method. Apparently, a large number of (very) small firms seems to behave like households who also typically claim not to use explicit financial methods when taking investment decisions.

Given the large number of firms not using any capital budget method, we use a bivariate probit model to explain, first, whether or not a firm is likely to use a

[18] Note that the reported payback periods would have been only marginally lower had we included other subsidies, i.e. not the EIA and EINP, as reported by the respondents.

[19] Note that the internal rate of return and the critical payback period are strongly related (see Sarnat and Levy, 1969). The CPBP can be replaced by a 'pseudo critical payback period' which is equal to $(1-(1+r)^{-n})/r$, where r is the required rate-of-return and n is the economic lifetime of the technology.

[20] The remaining 12% did not know if and what criterion their firm used and we add them to the category of not using any method. Note also that the high percentage of firms that claims not to use any method is not due to the presence of not-for-profit firms because the percentages are more or less similar in both subsamples.

capital budgeting method (in particular the *CPBP*), and, second, whether or not the firm was free riding on the subsidy program when making the investment.[21] Accordingly, we estimate the following model:

$$\begin{aligned} y_{i1} &= 1 \quad \left(\frac{X_{i1}'\beta_1}{\sigma_{i1}} + \varepsilon_{i1} > 0\right) \\ y_{i2} &= 1 \quad (X_2'(y_{i1}, z_i)\beta_2 + \varepsilon_{i2} > 0) \end{aligned} \tag{1}$$

where $\sigma_{i1} = z_i + \lambda(1 - z_i)$ and $X_2'(y_{i1}, z_i) = \left[\begin{array}{lll} [X_2^{1\prime} \quad X_2^{123\prime}], & y_{i1} = 1 & z_i = 1 \\ [X_2^{2\prime} \quad X_2^{123\prime}], & y_{i1} = 0 & z_i = 1 \\ [X_2^{3\prime} \quad X_2^{123\prime}], & y_{i1} = 0,1 & z_i = 0 \end{array}\right]$,

with $\begin{pmatrix} \varepsilon_1 \\ \varepsilon_2 \end{pmatrix} \sim N\left(\underline{0}, \left[\begin{array}{cc} 1 & \rho \\ \rho & 1 \end{array}\right]\right)$.

Here, β_1 and $\beta_2 = \left[\beta_2^1, \beta_2^2, \beta_2^3, \beta_2^{123}\right]$ are the regression coefficients of the explanatory variables of the first and second probit, respectively, z_i is a dummy indicating whether or not the firm is for-profit ($z_i = 1$) or not-for-profit ($z_i = 0$), λ captures any differences in variance between the for-profit and not-for-profit firms, and ρ is the correlation coefficient.

We estimate both a pooled and a non-pooled version of the model.[22] In the pooled version of the model we have $\beta_2^1 = \beta_2^2 = \beta_2^3 = 0$. In the non-pooled version of the model we split our sample into three groups: (1) rational for-profit firms ($y_{i1} = 1, z_i = 1$); (2) quasi rational for-profit firms ($y_{i1} = 0, z_i = 1$);[23] and (3) not-for-profit firms ($z_i = 0$)[24] Notice that our model is a recursive simultaneous-equations model with an endogenous set of (interacted) variables in the second probit where the endogenous nature of the variables on the right-hand side of the second equation can be ignored in formulating the log-likelihood (Greene, 2004,

[21] We have restricted the first probit to only those firms that claim to use a payback period. The very few firms using an internal rate of return are taken together with firms that claim not to use any method. Deleting these firms from our sample has no influence on our results (results available on request).

[22] We use the subscripts 1 and 2 for β and X to denote either the first or second equation. We use the superscripts 1, 2 and 3 to denote whether or not a specific variable appears only in a specific subgroup (explained later in more detail). The superscript 123 is used to denote a variable that appears in all subgroups.

[23] In the remainder of the paper firms using a capital budgetting method are called 'rational' firms, whereas firms not using any capital budgetting method are called 'quasi rational' firms.

[24] Unfortunately, in the non-pooled model data limitations prevent us from splitting the last group into rational not-for-profit firms and quasi rational not-for-profit firms.

715ff). This specification allows us to capture any correlation between unobserved variables (or characteristics) in both equations.

The first equation, which we subsequently refer to as the 'capital budgeting equation', explains whether a firm with certain observable characteristics, like turnover, number of employees and the sector in which they are active, uses a capital budgeting method. The model explicitly allows for differences in variance, measured through λ, between for-profit firms ($z_i = 1$) and not-for-profit firms ($z_i = 0$).The second equation, subsequently referred to as the 'rents equation', explains whether a firm is a free rider ($y_{i2} = 1$) or not ($y_{i2} = 0$).

When do we expect that a firm is more likely to be a free rider? We hypothesize that whenever firms are investing in more unprofitable technologies, i.e. in technologies with a higher payback period, the firm is less likely to be a free rider. In addition, we hypothesize that, due to the possibility of the firm being liquidity constrained, firms making expensive investments are less likely to be free rider. Finally, we expect that the probability that the firm is a free rider is increasing in the level of the *CPBP* as they are using a less stringent capital budgeting criterion.

4 Results

4.1 Pooled sample

Tables 4 (capital budgeting equation) and 5 (rents equation) together present the regression results for our sample. We start, for the sake of reference, with estimation results for the pooled sample (see Model (1) in these tables). According to our estimates, firms with a (relatively) large turnover in our sample are significantly more likely to use capital budgeting methods compared to firms with smaller turnovers. This finding is consistent with those of the survey by Graham and Harvey (2001), who found that larger firms use more sophisticated capital budgeting methods (although note that our sample falls more or less entirely within their 'very small firms' category). Furthermore, the probability of using capital budgeting methods differs significantly across sectors (after correction for size). Compared to horticulture, other firms are significantly less likely to use capital budgeting techniques.[25] Transport firms are least likely to use capital budgeting techniques.

[Insert Tables 4 and 5 around here]

[25] In Table 4 we have not reported the estimates for horticulture firms as they are all very small and insignificantly different from zero.

Our 'rents equation' for the pooled model (see column (1) in Table 5) clearly shows that the probability of the firm being a free rider decreases with the payback period (*PBP*) of the technology. This is as predicted: fewer firms will invest in technologies with high payback periods as they are not very profitable. Hence, the number of firms investing in such technologies without a subsidy can be expected to be small. According to this pooled model, neither the size of the investment nor the *CPBP* have an effect on the probability of the firm being a free rider. This is remarkable as one would expect a positive effect from the *CPBP* variable for firms that evaluate their decisions using a capital budgeting method. Note also that the correlation of the unobserved factors between the first and second equation (ρ) is 0.32 and highly significant. Finally, the variance of the unobserved factors for the 'capital-budgeting equation' is smaller for not-for-profit firms than for for-profit firms. Not-for-profit firms are more similar compared to the for-profit firms because they are predominantly found in the non-commercial services sector.[26] This illustrates that consistent estimation of the rent equation indeed requires our bivariate procedure. Taken together the findings for the pooled model are somewhat disappointing. However, the results also suggest that firm and technology characteristics can explain (at least to some extent) the variation in free riding across firms.

4.2 Non-pooled sample

As firms characteristics differ markedly in our sample, we more explicitly allow for variation in behavior between different types of firms and estimate a non-pooled version of our model dividing the sample in the three separate groups mentioned before: (i) rational for-profit firms using *CPBP*; (ii) quasi rational for-profit firms not using *CPBP*; and (iii) not-for-profit firms.[27] Models (2) and (3) in Tables 4 and 5 present the results of two specifications for the non-pooled estimation.[28]

From model (2) it is clear that the original result for the pooled sample is 'only' reproduced for the rational for-profit firms, whereas the results are very different for the other two groups. In particular, the probability of free riding for quasi

[26] In total we have 189 not-for-profit firms in our sample of which 140 are active in the non-commercial services sector and 49 in the commercial services sector.

[27] We also estimated our sample in four separate groups: (1) rational for-profit firms; (2) quasi rational for-profit firms; (3) rational not-for- profit firms; (4) quasi rational not-for-profit firms. Due to sample limitations, however, all results for the not-for-profit firms turned out to be statistically insignificant.

[28] We do not discuss the results of the capital budgetting equation for the non-pooled model as they are almost identical to the results for the pooled model.

rational firms in the for-profit sector does not depend on the payback period of the technologies.[29] We find evidence, however, that the probability of free riding depends on the 'physical' payback period, i.e. the payback period measured in physical terms and expressed in Euros per TJ (and that justifies the label quasi rational). For quasi rational firms the probability of being a free rider decreases with the physical *PBP*. This suggests a similar variation across quasi rational for-profit firms compared to rational for-profit firms: firms investing in less profitable technologies are less likely to be free riding. Interestingly, we find that the level of the investment affects the probability of free riding for quasi rational for-profit firms as well. The larger the investment, the smaller the probability that the firm is free riding. This is consistent with our hypothesis. An explanation might be that the capital budgeting process in quasi rational firms is less precise and that this causes them to be liquidity constrained.

Note that the variable *CPBP* is still not significant in Model (2). One reason could be that the effect of the *CPBP* on the probability of free riding interacts with the economic lifetime of a technology.[30] A higher *CPBP* might raise the probability that a firm is free riding, but only for investments with a similar economic lifetime. Interacting the *CPBP* reported by these firms with dummy variables indicating the economic lifetime of the investment (ELT10, ELT15 and ELT50 for technologies with a lifetime of respectively 10, 15 or 50 years), confirms our intuition (see Model (3) in Table 5). The coefficient of the *CPBP* now shows up statistically significant for two out of the three categories.

The results for the not-for profit sector are indeterminate and statistically insignificant. However, the coefficient for the level of the investment has the right sign and is much larger than the similar coefficient for the quasi rational for-profit firms. We expect the insignificance to be due to data limitations because the number of not-for-profit firms in our sample is relatively small. Finally, note that the correlation of the unobserved factors between the first and second probit (ρ) in the non-pooled model is 0.61, which is much higher than in the pooled model.

[29] This model is not included separately. The only difference with model (2) is a statistically insignificant coefficient for *PBP*.

[30] The economic lifetime of a technology is taken to be similar to the depreciation period allowed under Dutch accounting law.

4.3 Robustness

Questionnaires in general may suffer from policy response bias, i.e. respondents would anticipate potential negative effects of their answer on future policy decisions. In our case, firms might be inclined to answer that they have changed their decision to buy the energy-saving technology because of the subsidy, i.e. that they are not free riding. Otherwise the possibility to reap rents in the future might be reduced by the regulator in response. Our analysis, however, has focused on how firms frame their investment decisions and how this is linked to the choice of the regulator to provide subsidies on some technologies and not on others. Furthermore, if this response bias would differ systematically between the groups, this is likely to be captured by the fixed effects for each group.[31] Finally, we controlled for this potential problem in our survey by asking firms about their prime reason for investing in the energy-saving technology, and allow for potential underreporting as a covariate accordingly (see variable *UNDERREPORT* in Table 5). We suspect that firms that are primarily interested in obtaining the subsidy are more likely to respond strategically. From the firms in our sample, 14% answered that 'obtaining the subsidy' was their prime reason.[32] Firms providing this answer indeed systematically more often answer that their decision has been changed due to the subsidy as is clear from Table 5. This coefficient is strongly significant and robust across specifications and raises the probability that the firm is free riding considerably.

[Insert Figure 1 around here]

Another potential bias in our study is that the different groups of firms may have invested in technologies with different payback periods or, more generally, that some technologies drive our overall findings. As a first check we use our data on the payback periods of the technologies (see Figure 1). The cumulative density functions of the payback periods for the different groups do not differ substantially. It is clear that the bulk of the technologies has payback periods smaller than 10 years for all groups with the exception of the quasi rational for-profit firms who substantially more often invest in technology with longer payback periods, mostly insulation. In order to check whether insulation drives our results we re-estimated

[31] Notice that the rational for-profit firms are on average more likely to free ride than the other two groups as the coefficient of CONSTANT is positive and statistically significant.

[32] Other possible answers were an upgrade of a previous similar investment (25%), an upgrade of the entire production process and a cleaner environment (8%), regulation (3%) and better image (2%).

the model after deleting all observations on insulation from our data set.[33] In the case of for-profit firms the coefficient for *PBP* becomes marginally insignificant as does the coefficient for the physical *PBP*. But in no case do we observe a switch in the sign or magnitude of these coefficients.[34] So we conclude that insulation does not drive our results. More generally, the results are robust with respect to deleting all other technologies (on a one by one basis). Only in the case of High Efficiency boilers the coefficients for ELT10 and ELT50 become marginally insignificant.

Eligibility for the subsidy only applies if a particular technology is on the Energy-List. So this list contains information about the (physical) savings characteristics of the technologies allowing us to test more explicitly whether this kind of subsidy also has an effect on the information set of the regulated agent. If learning about the characteristics of technologies is costly, a subsidy may signal the importance of particular technologies and accordingly stimulate learning about new technologies (Wene, 2000; Newell et al., 2003). This hypothesis has been tested by asking the firms whether they have obtained knowledge about the subsidy at or after the time of the decision to invest (see variable *NO ATTENTION VALUE* in Table 5). These firms indeed are less likely to have changed their decision compared to firms with knowledge about the subsidy prior to the time of investment. A possible explanation for this result is that companies who knew about the (EIA or EINP) subsidy may have 'discovered' their investments by looking on the Energy-List. These investments may receive more support during the decision process or may be – on average – more profitable.

4.4 Policy implications

Selection bias might be a serious shortcoming of our sample if the investment behavior of firms in our sample is not representative for small firms in general. Indeed, the firms in our sample have all invested in these technologies with subsidy, so we cannot compare their behavior with firms that have invested in these technologies without subsidy or have not invested at all. However, even if the sample would not be representative for small firms in general, our results are still very useful for a regulator interested in improving adoption subsidy designs. Our results indeed demonstrate

[33] The number of observations is reduced from 862 to 655 by deleting all observations on insulation. Another way to check for robustness would be to interact the dummy for insulation with the three previously defined groups of firms. However, we have insufficient observations to allow for six instead of three groups of firms.

[34] Available on request from the authors.

that the choice of technologies on the Energy List matters for the effectiveness of the subsidy scheme. To illustrate we computed marginal effects (see Table 6). According to our estimates a 1% increase of the *PBP* reduces the probability that rational for-profit firm are free riding by 0.007%, whereas a 1% increase in the physical *PBP* reduces the probability that quasi-rational firms are free-riding by 0.004%. Moreover, a 1% increase in the size of the investment reduces the probability that a quasi rational for-profit firm is free-riding by 0.76%. Regarding firm characteristics, we found that a 1% increase in the number of rational firms decreases the number of firms that are free riding by 0.085%. The regulator cannot directly observe the type of firm (rational or not), but might use information such as the size and sector of the firm. Firms with a large (medium) turnover are 4% (1.6%) more likely to be free-riding compared to small firms. Moreover, firms active in the transport sector are almost 5% less likely to be free-riding compared to horticulture firms. Hence, we conclude that technology and firm characteristics can be used as conditioning characteristics to improve the effectiveness of a subsidy program.[35]

[Insert Table 6 around here]

5 Conclusion

In this paper, we showed - based on a unique micro dataset on adoption decisions of subsided technologies - that investment behavior of small firms differs markedly between different types of firms and characteristics of adopted technologies, resulting in a distribution of rents across firms and technologies. Our results contribute to the existing empirical literature by shedding new light on why firms invest in certain technologies, what role is played by subsidies and tax credits, and how policy instruments can be made more effective by reducing rents.

Using a dataset on individual investments in energy-saving technologies, we showed that (i) the probability that for-profit firms will invest in energy-saving technologies decreases with the payback period of the technology, whereas the probablity that not-for-profit firms will invest does not depend on the payback period of the technology; (ii) that firms using an explicit investment criterion are less likely to invest than firms not using an explicit investment criterion. In addition, we find that

[35] The Dutch regulator removed the technology light- weight semi trailers from the Energy List after our study was completed because it hardly had any incentive effect. In fact, the subsidy was even larger than the investment cost differential with its reference technology. Since the regulator has continued to screen and remove technologies from the Energy List.

the way in which firms frame their investment decision is correlated with observable characteristics like the size of the firm and the sector in which they are active. In our particular sample of firms about half claims *not* to use any capital budgeting technique to evaluate investment decisions. The other half computes economic consequences of an investment project explicitly, but mainly through the simplest of capital budgeting techniques, i.e. payback period (PBP). We find that larger firms are more likely to use the payback period as a capital budgeting technique and that the use of the payback period differs extensively between sectors. Agricultural and transport firms are much less likely to use a capital budgeting technique compared to horticulture firms. These results confirm our idea that the regulator may use both technology and firm characteristics as a screening device for reducing rent extraction. The use of an Energy List by the Dutch government is an interesting example in this respect.

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6 Tables and Figures

Table 1: Number and size of applications under the EIA

	Number of Applications	Amount claimed (mln euro)	Average investment
1997	10,366	430	41,500
1998	14,145	656	46,400
1999	17,408	587	33,700
2000	25,815	695	26,900
2001	28,139	1,058	37,600
2002	17,228	1,344	78,000
2003	15,518	834	53,700

Table 2: Technology characteristics

	Investment	Reference	Saving	Subsidy[1]	PBP[2]	N
	mln Euro	mln Euro	mln Euro	%	year	
Combined Heat and Power	493	0	112	18	4.2	50
Condenser	82	41	29	42	1.4	50
Draught sealing	87	0	2	18	36.6	5
Energy blinds	84	0	17	22	4.9	68
Energy conserving cooling and freezing equipment, type A	49	39	5	115	2.7	11
Energy conserving cooling and freezing equipment, type B	86	69	3	106	4.9	58
Energy efficient lightning	99	67	6	54	6.0	30
Frequency converter	38	0	12	20	3.2	66
Generic construction techniques	99	0	28	21	3.6	27
Generic equipm., processing techn.	474	0	288	17	1.8	26
Heat buffer	98	0	12	21	7.8	51
Heat pump	64	21	13	27	3.3	7
Heat recovery from ventilation air	130	0	38	18	13.4	10
Heat registration system	24	0	1	19	27.3	6
High efficiency boiler	112	75	5	54	7.9	93
High efficiency glass	282	231	4	93	14.5	8
Insulation	60	0	3	21	23.0	207
Leightweight semi-trailer	711	605	17	117	6.2	53
Weather dependent optimizer of non-residential heating	54	0	10	18	5.3	7
Wind turbine	715	0	94	18	7.6	18

Notes: [1] Percentage subsidy of additional investment costs

[2] Mean PBP (measured in years) calculated by dividing additional investment of technology by its yearly energy savings (in euros) using sector specific energy prices of 1999.

Table 3: Descriptive statistics1

Variable	Unit	Mean	SD	Min.	Max.
Decision not altered by subsidy	dummy	0.51	n.a.	0	1
Investment cost	1000 euro	172.8	487.5	56.5	6,872.5
Investment cost reference technology[2]	1000 euro	159.3	538.8	2.4	5,841.6
Energy saved per year:					
- monetary	1000 euro	27.4	112.6	3.2	2,492.7
- non-monetary	TJ	1.91	6.54	0.00	100.3
Price electricity	euro	16.9	2.7	7.6	26.5
Price of gas	euro	37.5	12.2	18.6	63.3
Payback period (*PBP*):					
- in years		9.8	9.1	0.8	41.7
- in Euro/TJ		149.7	120.7	15.0	445.0
EIA or EINP subsidy as % of investment	%	19.9	n.a.	13.7	26.4
PBP including EIA or EINP subsidy	year	9.4	9.6	-66.5	41.7
Estimated Economic lifetime	year	22.2	16.5	10.0	50.0
Critical payback period (*CPBP*)[3]	year	7.0	3.9	1.0	31.4
Obtained VAMIL-subsidy	dummy	0.18	n.a.	0	1
Obtained other subsidies	dummy	0.11	n.a.	0	1
No attention value	dummy	0.39	n.a.	0	1
Small to medium company[4]	dummy	0.25	n.a.	0	1
Medium company[4]	dummy	0.42	n.a.	0	1
Large company[4]	dummy	0.22	n.a.	0	1

Notes: [1] Summary statistics apply to 862 observations over the three-year period 1997-1999.

[2] Reference technology applies to 310 observations.

[3] Critical payback period applies to 384 observations.

[4] Turnover small to medium companies below 0.45 mln €; medium companies between 0.45 and 4.5 mln €; large companies more than 4.5 mln €.

Table 4: Results Capital Budgeting Equation

	(1)	(2)	(3)
	Pooled	Non-Pooled	Non-Pooled
MEDIUM TURNOVER	0.21 ***	0.18 **	0.18 **
	(2.77)	(2.40)	(2.47)
LARGE TURNOVER	0.46 ***	0.45 ***	0.46 ***
	(3.57)	(3.57)	(3.67)
INDUSTRY	−0.37 **	−0.36**	−0.35**
	(2.21)	(2.22)	(2.20)
COMMERCIAL TRADE	−0.42 ***	−0.36**	−0.38***
	(2.71)	(2.44)	(2.57)
TRANSPORT	−0.63 ***	−0.58***	−0.61***
	(3.37)	(3.22)	(3.38)
COMMERCIAL SERVICES	−0.41 ***	−0.37***	−0.36***
	(2.92)	(2.79)	(2.75)
NON-COMMERCIAL SERVICES	−0.34 ***	−0.33***	−0.34***
	(3.04)	(3.02)	(3.07)
FOOD	0.37 *	0.39 **	0.41 **
	(1.75)	(1.97)	(2.07)
AGRICULTURE	−0.43 ***	−0.42***	−0.42***
	(4.12)	(4.14)	(4.22)
Variance not for-profit firms	0.54 ***	0.54 ***	0.57 ***
Capital Budget equation	(2.50)	(2.54)	(2.56)

Notes: dependent variable is USES CRITICAL PAYBACK CRITERION;
This equation is estimated jointly with the Rents equation (see Table 5);
t-statistics within parenthesis. ***[**](*) denotes significance at 1[5](10) percent level.

Table 5: Results Rents Equation

	(1)	(2)	(3)
	Pooled	Non-Pooled	Non-Pooled
Constant	0.14 (1.63)*		
PBP	−0.01 (2.92)***		
SUBSIDY	−0.87 (1.55)		
CPBP	0.01 (0.92)***		
(1) Rational for-profit firms			
Constant		0.47 (3.70)***	0.49 (3.35)***
PBP		−0.03 (2.90)***	−0.03 (2.54)***
INVESTMENT		0.39 (0.49)	0.72 (0.82)
CPBP		0.22 (1.50)	
CPBP*ELT10			0.05 (2.12)**
CPBP*ELT15			0.00 (0.19)
CPBP*ELT50			0.04 (1.97)**
(2) Quasi rational for-profit firms			
Constant		−0.05 (0.32)	−0.08 (0.52)
PHYSICAL PBP		−0.02 (2.36)***	−0.02 (2.25)**
INVESTMENT		−3.24 (2.18)**	−3.25 (2.19)**
(3) Not-for-profit firms			
Constant		0.02 (0.14)	0.02 (0.14)
PBP		0.00 (0.32)	0.02 (0.12)
INVESTMENT		−5.53 (1.32)	−5.26 (1.28)
UNDERREPORT	−0.62 (4.80)***	−0.54 (4.48)***	−0.55 (4.61)***
NO ATTENTION VALUE	0.19 (2.13)**	0.20 (2.39)***	0.19 (2.33)***
Rho	−0.32 (3.71)***	−0.61 (6.25)***	−0.64 (6.78)***
Log L	1139	1123	1120

Notes: dependent variable is WOULD HAVE MADE THE INVESTMENT WITHOUT THE SUBSIDY; This equation is estimated jointly with the Capital Budgeting equation (see Table 4); t-statistics within parenthesis. ***[**](*) denotes significance at the 1[5](10) percent level.

Table 6: Marginal Effects Bivariate Probit

Capital Budgeting Equation		*Rents Equation*	
Dummy variables[1]		Dummy variables[1]	
MEDIUM TURNOVER	0.016**	FOR PROFIT	−0.010
LARGE TURNOVER	0.039**	UNDERREPORT	−0.123**
INDUSTRY	−0.092**	NO ATTENTION VALUE	0.042**
COMMERCIAL TRADE	−0.032**	USES CPBP	−0.085**
TRANSPORT	−0.047**	Continuous variables	
COMMERCIAL SERVICES	−0.030**	INVESTMENT − rational for-profit	0.149
NON-COMMERCIAL SERVICES	−0.030**	INVESTMENT − quasi rational for-profit	−0.764**
FOOD	−0.033**	INVESTMENT − not-for-profit	−1.180
AGRICULTURE	−0.034**	PBP −rational for-profit[2]	−0.007**
		PHYSICAL PBP −quasi rational for-profit[3]	−0.004**
		PBP − not-for-profit	0.000
		CPBP*ELT10	0.010**
		CPBP*ELT15	0.001
		CPBP*ELT50	0.005

Notes: ** denotes significance within two sided 5% confidence interval.

[1] changes calculated in percentage points.

[2] percentage change of in levels.

[3] based on physical PBP of technologies.

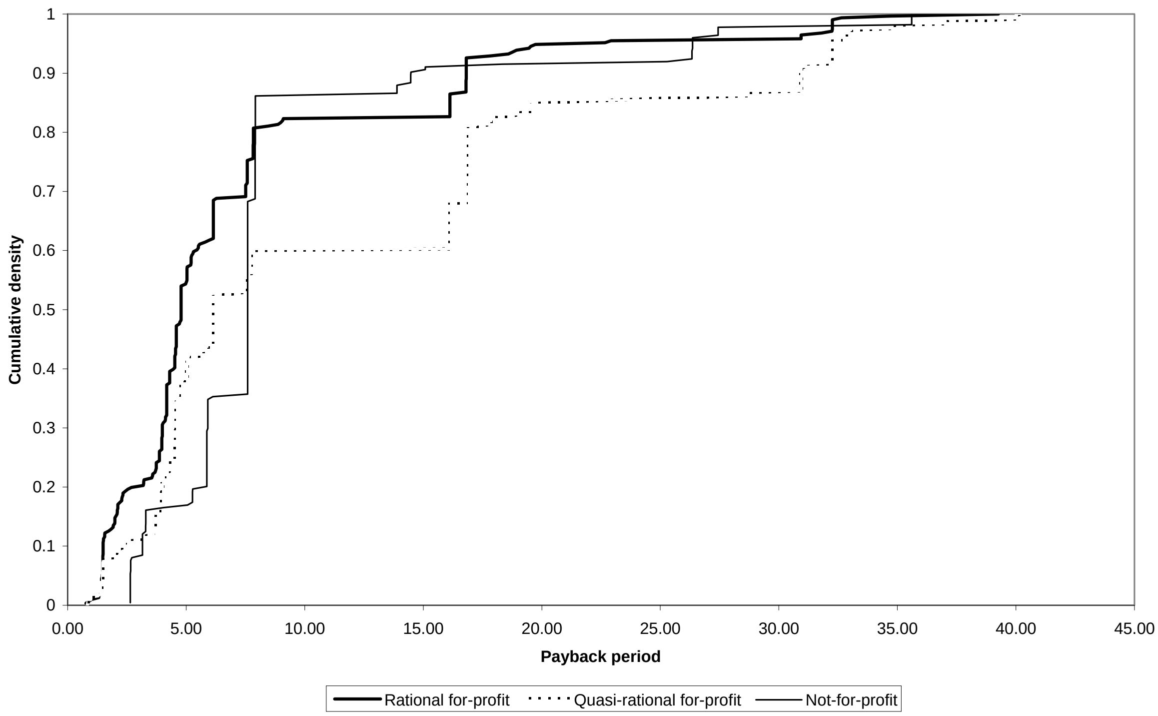

Figure 1: Cumulative density function of payback periods of adopted technologies for different types of firms.

Appendix A Marginal Effects

We are interested in the effect of (observable) firm and technology characteristics on the probability of free-riding. The conditional mean is:

$$\begin{aligned} E\{y_2|X_1,X_2\} &= P\{y_1=1\}E\{y_2|y_1=1,X_1,X_2\}+P\{y_1=0\}E\{y_2|y_1=0,X_1,X_2\} \\ &= \Phi(X_1'\beta_1,X_2'\beta_2,\rho)+\Phi(X_1'\beta_1,-X_2'\beta_2,-\rho) \end{aligned}$$

Marginal effects are calculated as in Greene (2004, p. 716). For continuous variables this conditional mean function is differentiated to calculate te marginal effects. For binary variables the conditional mean function is computed with this variable set to one and zero. The marginal effect is the difference between these values. Finally, the marginal effect of using a payback period on the decision (not) to buy is calculated as $P\{y_2=1|y_1=1,X_1,X_2\}-P\{y_2=1|y_1=0,X_1,X_2\}$. Standard errors for the estimated marginal effects are calculated by using a Monte Carlo procedure. For each marginal effect 5000 draws were taken from the bivariate normal distribution (using the Choloski transformation: see Train, 2003). For each of these draws we computed the marginal effect. Finally, we took the 95% confidence interval of the resulting distribution.