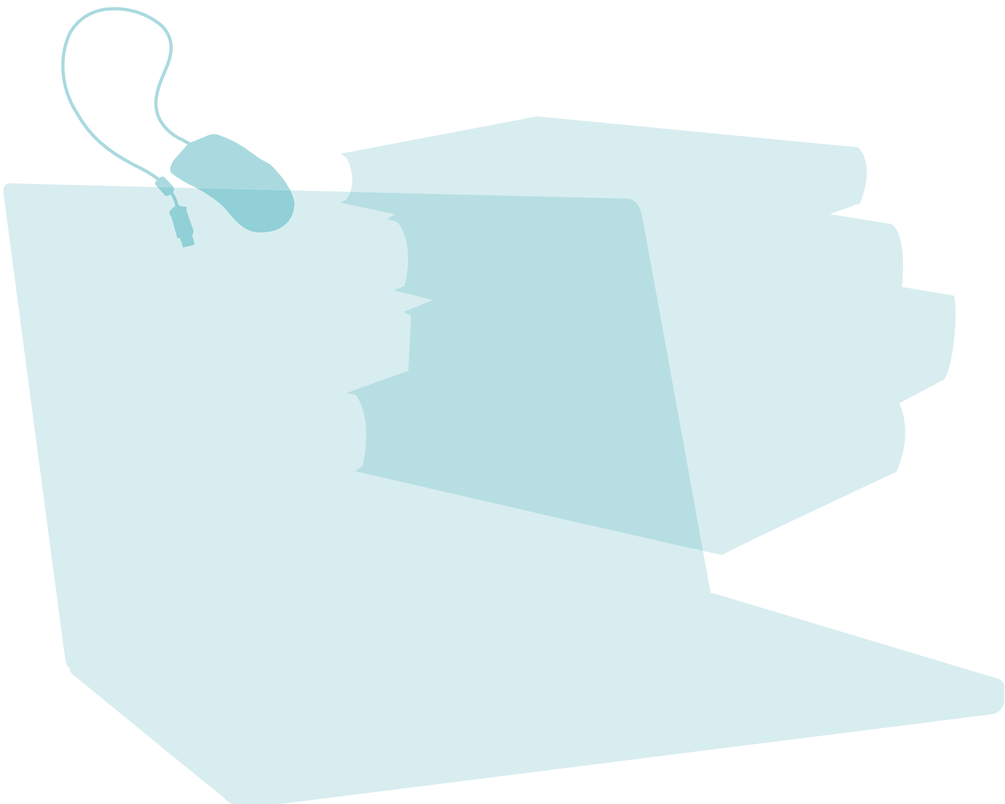
Linking ICT related Innovation Adoption and Productivity:

results from micro-aggregated versus firm-level data



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Explanation of symbols

.	data not available
*****	provisional figure
******	revised provisional figure (but not definite)
x	publication prohibited (confidential figure)
–	nil
–	(between two figures) inclusive
0 (0.0)	less than half of unit concerned
empty cell	not applicable
2012–2013	2012 to 2013 inclusive
2012/2013	average for 2012 up to and including 2013
2012/’13	crop year, financial year, school year etc. beginning in 2012 and ending in 2013
2010/’11–2012/’13	crop year, financial year, etc. 2010/’11 to 2012/’13 inclusive

Due to rounding, some totals may not correspond with the sum of the separate figures.

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Linking ICT related Innovation Adoption and Productivity:
results from micro-aggregated versus firm-level data

George van Leeuwen[a,b] and Michael Polder[a]

Summary:

E-business systems are increasingly considered as important examples of ICT related innovations embodied in software applications, the adoption of which is essential for capturing the fruits of several ICT externalities. For analysing the importance of this type of embodied technological progress several routes are open. One route is to look at the different types data that can be used. In this paper we apply the same modelling strategy to two types of data: 1) cross-country-industry micro-aggregated data obtained after applying Distributed Micro Data Analysis (DMD) and 2) firm-level data, in this case for the Netherlands. Today, the econometric analysis based on firm-level data is often more advanced and more complicated from an econometric point of view than the analysis on aggregated data. We show that DMD can be extended to enable the estimation of more complicated models that feature recent advances in micro-econometric analysis on firm-level data. Our application concerns the innovative use of e-business systems by firms. Using a rich set of cross-country-industry data constructed and tailored by DMD for this purpose, we analyse the adoption of three e-business systems (Enterprise Resource Planning, Customer Relationship Management, Supply Chain Management. We investigate the complementarities in joint adoption and the productivity effects of adopting systems simultaneously or in isolation. The same exercise is repeated on firm-level data for the Netherlands. Our example illustrates that international benchmarking with more elaborate models on cross-country-industry panel data is feasible after using DMD to tailor the underlying firm-level data for specific research questions. This is an important result in the light of the restrictions on pooling cross-country micro data due to confidentiality rules. We find that the results are more diverging for the estimation of complementarities at the adoption stage than for the productivity effects of (joint) adoption. This result implies that measurement error and unobservable heterogeneity play a greater role when explaining adoption pattern at the firm-level than at the aggregate level.

Keywords: DMD, ICT, innovation, innovation complementarities, productivity

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1. Introduction

Firms use ICT in many innovative ways. Besides the investment in computer hardware, these innovative applications require the use of specific software for making ICT work. It is widely acknowledged that the main feature of Information Technology embedded in the use of computers lies in the creation and exploitation of network externalities, both within the firm and between firms by crossing the boundaries of firms, industries or even countries. Nowadays, investing in computer hardware is simply nothing more than a necessary (but basic) prerequisite for enabling this potential of ICT. The real issue today is how hardware and software are combined for managing and exploiting the many potentials of ICT usage.

The importance of this issue is also reflected in new statistical measures aimed at providing a more comprehensive understanding and assessment of ICT usage at the firm level. Since 2007 new questions concerning so-called e-business systems (or Enterprise Systems (ES)) are included in Eurostat's Community Survey On ICT Usage And E-Commerce In Enterprises. This (new) measurement goes beyond the earlier collected e-commerce variables and data collected on the readiness of ICT usage, and in particular concern: 1) the use of Enterprise Resource Planning (ERP), 2) the use of Customer Relationship Management (CRM), 3) the use of Supply Chain Management (SCM), 4) the use of Automated Data Exchange (ADE), and 5) the use of internal linkages of ICT systems. These variables relate directly to internal (ERP, other internal linkages), and external linkages of the firm (CRM, SCM, ADE), where the abbreviations refer to the naming of the corresponding variables collected in the ICT usage survey.

Today, Enterprise Systems (ES) are broadly considered as important examples of ICT related innovations that are aimed at capturing the full potential of ICT externalities. The literature on the benefits and effectiveness of ES for firm performance is rather extensive, (see Zand (2011) and the references therein for a detail overview). Nevertheless, there remains a lack of understanding of how and why different ES are combined to improve firm performance. The reason for this is that many studies focus on a single ES and/or use case studies for a limited number of firms or special surveys for a single sector. In contrast, and because of their relative novelty, these new measures of ICT usage have not been applied or analysed extensively in the econometric literature. Some notable exceptions are Aral et al. (2006) and Zand (2011).

For analysing the importance of ES several routes are open. One route is to look at the way the available data can be used. In this paper, we make a further step in attempting to fill the gap between theory and empirics by extending the use of Distributed Micro Data analysis (DMD, see Bartelsman, 2004). DMD is a well-established tool for constructing harmonized cross-country-industry data for enhancing international benchmarking of productivity analysis, often obtained after linking firm-level data from different sources., In almost all cases the analysis takes the form of a descriptive analysis of micro-linked data, enhanced with the (remotely carried out) estimation of relatively simple reduced-form productivity regressions according to a common methodology.

By contrast, much econometric analysis on firm-level data is more advanced from an econometric point of view. Due to methodological complexities, recent developments in firm-level based micro-econometric research cannot be easily applied in benchmarking across countries, or seem to be less useful when applied to micro-aggregated cross-country-industry data constructed to circumvent confidentiality issues of using the pooled micro-data directly.

In this paper we present a comparison of the two alternatives. We show that DMD can be extended to enable the estimation of more advanced micro-econometric models., in particular the research aimed at disentangling the impact of innovation on productivity into 1) the innovation adoption decisions of firms and 2) the impact of the adoption of several innovation modes on productivity (e.g. Crépon et al. 1998; Van Leeuwen et al. (2013); Hall et al. (2012)).

Our application concerns the innovative use of e-business systems by firms. Following the mainstream research on innovation complementarities (Milgrom and Roberts, 1990; Milgrom and Roberts, 1995) and using a rich set of cross-country-industry data constructed by DMD for this purpose, we analyse the adoption of three types of ES (ERP, CRM, SCM), the complementarities in joint adoption and the productivity effects of adopting systems simultaneously or in isolation. To this end we implement a model proposed by Lewbel (2007) for solving the coherency and incompleteness problem when estimating systems of adoption equations with dummy endogenous variables. Moreover, we account for the fact that the innovation adoption is endogenous to the productivity or the overall efficiency of firms.

We demonstrate that by cleverly constructing sub-aggregates from the underlying micro data, DMD can be applied to mimic this mainstream of micro-data based empirical research. This allows for cross-country benchmarking. Furthermore, we compare the DMD-results with the results for the same application on firm-level data for the Netherlands. Our example illustrates that international benchmarking for more elaborate models on cross-country-industry panel data is feasible after using DMD to tailor the underlying firm-level data for specific research questions. In this way our approach can be labelled as *pseudo-micro data analysis* of ICT related innovation adoption and productivity.

The plan of the paper is as follows. Section 2 provides the theoretical background. Section 3 builds up the empirical model, looking at adoption stage of ES, and their ultimate productivity effects and the econometric issues involved. Section 4 describes and summarizes the data. Section 5 presents the results for the adoption models and production function estimations. Finally, section 6 concludes.

2. Some theoretical background

The use of ICT allows firms to share and gather information more easily, both internally and externally, and thereby to work more efficiently. Enterprise Systems are a well-chosen example of this particular enhancing effect of ICT embodied in three types of specific software:

– Enterprise Resource Planning (ERP) software typically integrates the data management for planning, procurement, manufacturing, sales, marketing, customer relationship, finance and human resources;

– Customer Relationship Management (CRM) software supports ICT intensive business activities that aim to collect, integrate, process and analyse information related to a firm's customers;

– Supply Chain Management (SCM) software is used to share automatically electronic information about procurement, manufacturing, sales, orders, and inventory with customers and suppliers, in order to coordinate the availability and delivery of products or services to the final consumer.

Figure 1. Supply Chain Macro Processes in a firm

Supplier	*Firm*	*Customer*
SRM	**ISCM**	**CRM**

– SRM: Supplier Relation Management
– ISCM: Internal Supply Chain Management
– CRM: Customer Relationship Management

Source: "Supply Chain Management: Strategy, Planning and Operation", 2010, Prentice-Hall, New Jersey, USA.

Figure 1 presents a stylized representation adopted from the text-book literature on Supply Chain Management. From the viewpoint of the full chain, SCM is the most encompassing technology applied to manage the flow of all information and all resources to maintain or increase responsiveness to (changes in) customer demand. It includes processes such as marketing, pricing, order management, production planning, replenishment of all stocks and procurement and the resources to streamline all functionalities . It is far more encompassing and advanced than the use of systems for electronically linking invoicing, accounting or payment, which typically are internal functions that can be automated to various degrees. The presentation serves to demonstrate that SCM software is an encompassing ES, but also that a sharp demarcation of software suites is problematic from an operational as well as from a statistical (measurement) point of view on the various processes. For example, firms that have adopted full SCM probably combine software modules that manage all processes simultaneously. ERP software may even be the backbone for the other two processes depicted in the figure (SRM and CRM). For example, ERP software developed by the company SAP is very modular and the full suite has many functionalities. Nevertheless, some modules of the full suite may not be installed (see Hitt et al., 2002).

The general feature is that each type of software typically employs databases as a repository of information and that databases constructed for several purposes can be linked by different software modules and ICT hardware systems to embed specific functionalities in the organisation. In Eurostat's ICT usage survey, the emphasis is on the software aspects of the various processes. In our application, innovation adoption concerns the application of specific modules of software suites for use for ERP, CRM and SCM processes.

This leads to some initial conjectures on the possible complementarity or substitutability of adoption decisions: 1) CRM and ERP software modules may be complementary to the implementation of full SCM processes, 2) implementing SCM software modules may be a substitute for implementing CRM - as well as ERP software modules, and 3) ERP and CRM software adopted simultaneously may well together form a (restricted) substitute for the functionality of the full implementation of SCM software.

The adoption of each of the three systems (or software suites) can be analysed in isolation. Zand (2011) advocates an approach in which the adoption of different systems is analysed simultaneously because the different modules of software suites can be complementary, cover different domains (units) of the organisation and thus can have a different impact on the overall efficiency of firms.

However, it is by no way guaranteed that even the joint implementation of the various software suites add to an increase of ICT related business value. For example the implementation of an ERP system is a very expensive and complex task which asks for high implementation costs for consulting, business process redesign (BPR), data conversion, training and testing etc. For this reason, changes in e-business processes are often referred to as ICT-enabled organizational change (Falk, 2005).

In many cases the implementation of ES software should be backed up with considerable organizational changes, covering all organizational domains involved to capture the full fruits of their functionalities. In many cases these software suites are purchased "from the shelf" and are not developed by the firm itself.

Davenport (1998) points to some negative effects of a large scale implementation of built-in generic functionality based on best practices that is embedded in the software and which may not fit into the individual practices of the implementing organization. In this sense the implementation of the different types of software can lead to a misfit if the organizational structure has not been tailored to their use or the attitude towards technology and skills of employees is insufficient (see e.g. Falk, 2005, for a discussion of ERP implementation failures). This view on the effectiveness of ES software calls for controlling for the existing differences in ICT readiness and the emergence and relative importance of ICT driven e-sales and e-purchasing when assessing the productivity impact of using ES systems.

The broadness of the potential benefits of the application of the three software implementations for enhancing ICT related process innovation and efficiency raises severe complications for judging their effectiveness on the overall performance of firms. This is also reflected in the literature. In general the evidence reported in the literature is predominantly qualitative in nature. In many cases such research takes the form of case studies devoted to the functioning of a single ES system and often boils down to appraising the response of stakeholders to very specific surveys. Many articles published in the Management Science literature are based on the results of case studies targeted at the managerial issues and the implications of the adoption of software modules that are the subject of investigation.

Indeed, the literature that reports empirical evidence of the effects of investing in ES software on firm performance is very scarce. The great majority of studies that looked into the impact of ES-systems on productivity consists of case studies or reviews of case studies and mainly for US firms. Very few studies empirically tests the productivity impact using representative datasets (Falk, 2013). Some notable examples are worth mentioning. Hitt et al. (2002) report results from reduced-form productivity estimates of implementing ERP software on different (large) subsamples. They conclude that firms that invest in ERP show better performance across a wide variety of firm performance measures. For a much smaller dataset, the role of ICT related process outsourcing and plant performance is investigated in Bardhan et al. (2006). They found that firms that invested more in ICT are likely to be more engaged in outsourcing and that ICT investment and outsourcing reduces plant cost of goods sold and improves the quality of output. Finally, using a sample of about 525 firms, Shin (2006) shows that Groupware (software that includes functionalities of ERP, CRM and SCM software) or SCM software alone raise the productivity of SME firms. Falk (2005) reports results for the productivity impact of implementing ERP systems. Using data on the electronic sales and purchases of watches for Germany, France, Italy and the UK, he found a significantly positive contribution of ERP- linked organizational change on productivity. Aral et al. (2006) find that ERP is a pre-requirement for successful investment in other systems like CRM and SCM. Finally, more recently, Brynjolfsson et al. (2011) find that firms that make data-driven decisions attain 60% higher profitability and 50% higher market value from ICT.

3. Empirical model

In this paper we follow the same empirical strategy as in Polder et al. (2010) but we extend the adoption model used there, following Van Leeuwen and Mohnen (2013), to account for complementarity or substitutability at the adoption stage.

We start the exposition by presenting an adaptation of the model given in Heckman (1978) for the three-dimensional case. Omitting firm and time subscripts for the ease of exposition, this model reads:

$$y_1^* = \alpha_{12}y_2 + \alpha_{13}y_3 + \beta' x_1 + \mu_1$$

$$y_2^* = \alpha_{21}y_1 + \alpha_{23}y_3 + \beta' x_2 + \mu_2 \tag{1a}$$

$$y_3^* = \alpha_{31}y_1 + \alpha_{32}y_2 + \beta' x_3 + \mu_3$$

The dependent variables in (1a) refer to the profit or utility values of implementing ERP, CRM and SCM respectively (labeled y_1^*, y_2^*, y_3^*) and the *x*'s refer to the exogenous variables that are assumed to explain ES adoption, including a constant term. To circumvent possible endogeneity problems we will use predetermined (lagged values) of explanatory variable as much as possible[1]. The μ parameters are representing *i.i.d.* disturbances. Their interpretation and implementation will be discussed later on.

The y_i^* in (1a) should be treated as latent continuous endogenous variables. For each of these the events $y_i^* < 0$ or $y_i^* > 0$, $i = 1,\ldots,3$ are observed. Let $I(\cdot)$ denote the indicator function, which equals 1 if the condition in $I(\cdot)$ is true, and 0 otherwise. Then $y_i \equiv I(y_i^* > 0)$, reflects whether a firm has adopted a certain type of ES system y_i ($i = 1,\ldots,3$). As an example consider the first equation of (1a). If a firm has adopted ERP, then $y_1^* > 0$, and hence

$y_1 \equiv I(y_1^* > 0) = 1$, and

$\mu_1 < \alpha_{12}y_2 + \alpha_{13}y_3 + \beta' x_1$.

By contrast, if the same firm has not adopted ERP, then $y_1^* < 0$, and hence

$y_1 \equiv I(y_1^* > 0) = 0$, and

$\mu_1 < -(\alpha_{12}y_2 + \alpha_{13}y_3 + \beta' x_1)$.

From (1a) we can therefore derive that

$$\Pr(y_1 = 1) = \Pr(\mu_1 < \alpha_{12}y_2 + \alpha_{13}y_3 + \beta' x_1).$$

$$\Pr(y_2 = 1) = \Pr(\mu_2 < \alpha_{21}y_1 + \alpha_{23}y_3 + \beta' x_2) \tag{1b}$$

$$\Pr(y_3 = 1) = \Pr(\mu_3 < \alpha_{31}y_1 + \alpha_{32}y_2 + \beta' x_3)$$

By doing so, (1b) becomes the empirical counterpart of (1a). Equations (1b) constitute a system with dummy endogenous explanatory variables, and be used to address some interesting research questions associated with the use of the e-business systems:

[1] For reasons that will be explained later on it is not possible to construct lagged variables for the DMD data. It is expected that the endogeneity issue is less harmful for this type of data than for firm-level data.

– what determines the adoption of such systems?

– are there complementarities between the adoption of various systems or are they substitutes?

– are there externalities in the sense that firms learn from best practices?

– conditional on adoption: are there productivity effects of adopting such systems, and do these effects depend on the combination of ES systems used?

We first focus on adoption models for ERP, CRM, and SCM, integrating aspects of externalities like the distance-to-frontier, and complementarity or substitutability in adoption. An important aspect is that we demonstrate how to use the micro-aggregated cross-country dataset for pseudo-micro analyses. A firm can be classified according to which of these systems it has adopted, which we call its e-business profile. In the cross-country-industry data, summary statistics for selected explanatory variables by e-business profiles have been constructed, which allows the estimation of discrete choice models using the data as pseudo-micro data. For example, the (ERP, CRM, SCM) = (0,1,1) profile would translate into a set of observations with ERP = 0, CRM = 1 and SCM = 1, and the means of the explanatory variables for this profile enter as mean values for the explanatory variables in (1b). Naturally, this approach implies the need of some kind of weighing since not every profile has the same number of observations in the country-industry micro-data underlying DMD.

Finally, and similar to the innovation profiles in e.g. Polder et al. (2010), the e-business profiles are included in productivity regressions. The coefficients on the profiles can be used to assess which combinations contribute to productivity (growth) and which types of e-business are possibly complementary with respect to productivity, taking also into account the endogeneity of ES adoption for productivity. The difference with the earlier study is that our earlier research used micro-level data for the Netherlands, whereas here we used micro-aggregated data for industries and 15 European countries and compare the results for these clustered data with the results for Dutch firm-level data.

3.1 Assessing complementarities at the adoption stage

It can be easily seen that removing the endogenous regressors of (1b), i.e. by imposing zero restrictions for all parameters α_{ij} (i.e. $\alpha_{ij} = 0$, $i, j = 1,..3$; $i \neq j$). leads to a trivariate Probit model that is similar in structure as the models applied in our previous research (see Polder et al., 2010). Methods for estimating such models are readily available (see Capellari and Jenkins (2003, 2006) and Train (2003)).

In this study, however, we will adopt the full specification of (1b) for the reason that we also like to investigate the importance of complementarity or substitutability for the three ES systems at the adoption stage. We label these "ex-ante" complementarity and substitutability because these reflect the innovation strategies and managerial decision making that have resulted in certain adoption combinations which are observed in the data.

If we consider the adoption of ES as an instance of ICT enabled organizational innovation, then the three types of innovation are likely to be interrelated in the sense that the return to investing in a certain type of ES could depend on the adoption of the other systems for reasons of complementarity or substitutability between them. It is well documented in the econometric literature (see e.g. Heckman (1978), Tamer (2003), Lewbel (2007)) that the estimation of a trivariate probit with endogenous dummy variables raises severe problems of identification. There can be no solution (in which case the system is said to be incoherent) or multiple solutions (in which case it is said to be incomplete). The empirical literature offers several solutions to this problem. In general, these solutions boil down to imposing zero restrictions on the coefficients of some of the binary endogenous explanatory variables or by relying on recursive or triangular systems in which one of the choices is assumed to be leading (see for a discussion of completeness and coherency section 2 of Tamer (2003)). One way to avoid incoherency and incompleteness is to start from a McFadden (1973) solution by considering a multinomial choice problem based on a random utility model. This framework has been proposed more recently by Lewbel (2007) and adapted by Miravete and Pernías (2006) and Kretschmer et al. (2012).

Let the total utility (in this case profit) be

$$\begin{aligned} V &= V(y_1, y_2, y_3) = \\ &(\beta_1' x_1 + \alpha_{12} y_2 + \alpha_{13} y_3 + \varepsilon_1) y_1 + \\ &(\beta_2' x_2 + \alpha_{21} y_1 + \alpha_{23} y_3 + \varepsilon_2) y_2 + \\ &(\beta_3' x_3 + \alpha_{31} y_1 + \alpha_{32} y_2 + \varepsilon_3) y_3. \end{aligned} \tag{2}$$

The dichotomous variables for the three types of innovation are given by $y_i (i = 1,2,3)$. There are in total eight possible combinations of enterprise systems yielding respectively the following profit outcomes:

$$V(0,0,0) = 0 \tag{2a}$$

$$V(0,0,1) = \beta_3' x_3 + \varepsilon_3 \tag{2b}$$

$$V(0,1,0) = \beta_2' x_2 + \varepsilon_2 \tag{2c}$$

$$V(0,1,1) = \beta_2' x_2 + \beta_3' x_3 + (\alpha_{23} + \alpha_{32}) + \varepsilon_2 + \varepsilon_3 \tag{2d}$$

$$V(1,0,0) = \beta_1' x_1 + \varepsilon_1 \tag{2e}$$

$$V(1,0,1) = \beta_1' x_1 + \beta_3' x_3 + (\alpha_{13} + \alpha_{31}) + \varepsilon_1 + \varepsilon_3 \tag{2f}$$

$$V(1,1,0) = \beta_1' x_1 + \beta_2' x_2 + (\alpha_{12} + \alpha_{21}) + \varepsilon_1 + \varepsilon_2 \tag{2g}$$

$$\begin{aligned} V(1,1,1) &= \beta_1' x_1 + \beta_2' x_2 + \beta_3' x_3 \\ &+ (\alpha_{12} + \alpha_{21}) + (\alpha_{13} + \alpha_{31}) + (\alpha_{23} + \alpha_{32}) + \varepsilon_1 + \varepsilon_2 + \varepsilon_3. \end{aligned} \tag{2h}$$

The “complementarity parameters” α_{ij} and α_{ji} are placed in parenthesis because only their sums can be identified.[2] If $\alpha_{ij} + \alpha_{ji} > 0$ ($\alpha_{ij} + \alpha_{ji} < 0$), the corresponding pair of innovations are complements (substitutes). The model is complete because (latent) profitability/utility is specified for all possible strategies and coherent because every strategy should have a latent profit or utility that exceeds the profits/utilities of all other strategies. As pointed out by Lewbel (2007), the difference with respect to the traditional multinomial choice framework is that we do not have a separate specification for $V(1,1,1)$ but instead we use (2a)-(2h) derived from the same model for the total latent profit function. To our knowledge this model has not been put to the empirical testing for more than two strategies because of computational difficulties.[3] We refer to Annex A for a more detailed account of the empirical implementation.

The ε_i's are random errors that are assumed to be jointly normally distributed. These reflect that there may be other mediating factors at work, known to the firm but not to the researcher. Every strategy chosen may be may be part of a broader strategic plan that also covers other innovation strategies, such as strategic choices on product innovation, process innovation, organizational or marketing innovations.

Such unobservable factors may hide unobserved firm-specific effects contributing to the profitability or utility of adopting various types of ES. An example is the dependence on the (initial) state of the quality of labor. Moreover, the importance of such effects may change over time and in a way that is common for all adoption decisions. See Athey and Stern (1998), Miravete and Pernías (2006) and Kretschmer et al. (2012) for a discussion of these issues.

These considerations call for a more detailed specification of the disturbance terms. Taking a specific firm *f* in year *t* as the starting point, we thus use

$$\varepsilon_i = \varepsilon_{f,i} + \varepsilon_{t,i} + \varepsilon_{f,t,i}, \qquad (3)$$

as a specification of the disturbance term for the adoption of ES system *i*, and where $\varepsilon_{f,i}$ is a firm-specific fixed effect, $\varepsilon_{t,i}$ a time-specific effect and $\varepsilon_{f,t,i}$ the idiosyncratic part of the disturbance term for explaining the adopting of system *i* by firm *f* in year *t*.

As discussed in Athey and Stern (1998) and Kretschmer et al. (2012), the issue of how to deal with such unobserved heterogeneity is far from trivial when analyzing any combination of adoption decisions. At least, this calls for an estimation approach that takes into account the correlations between the disturbances of the models for the various adoption combinations at stake. This discussion can be extended further by including measurement error. In general measurement errors plague empirical research such as reported here. Therefore, one can expect that measurement

[2] We recall that if the α_{ij}'s are equal to zero, of the model reduces to a standard trivariate Probit model.

[3] See Miravete, E. and J. Pernías (2006) for the application of similar model in the bivariate case.

error may play a role in this research, not at least due to the problems concerning the demarcation of the different ES systems as already mentioned in section 2. Such measurement errors, to the extent that these are more or less random, will be confounded in the disturbance terms of (1b). However, it is also well-known that measurement errors may be more severe if these concern the measurement of explanatory variables of regression models. Again such measurement error may be completely random or not. Nevertheless, even if completely random, such measurement errors contribute to the correlation between the idiosyncratic parts and the included regressors in (1b) and this may, in turn, give rise to biased estimates. It is well-known that the magnitude and direction of such measurement error biases are dependent on the (unknown) signal-to-noise ratios occurring for the measures used.

Unfortunately it is not possible to account for all problems simultaneously. We have adapted the estimation routines for Multivariate Probit Models (see Cappellari and Jenkins (2003 and 2006)) to account for complementarity or substitutability of (ICT enabled) innovation modes, and to allow for an unrestricted specification of the correlations between the disturbance terms of the three adoption decisions that are the focus of this research and in line with Kretschmer et al. (2012).

Thus, unobserved heterogeneity and measurement error can be dealt in firm-level estimations within this framework. For this reason we also apply the same model to micro-aggregated cross-country-industry data constructed from DMD. It is expected that the influence of measurement error is mitigated if we use micro-aggregated data (see also Bartelsman et al. (2009) on the issue of measurement error in DMD data). For instance, under certain assumptions, firm and time specific effects can be captured or summarized conveniently by including country, industry and time dummies in our models, since essentially the country-industry-time average become the unit of analysis. We believe that it makes sense to have a comparison of these two approaches, because this enables us to learn from the differences in results.

3.2 Productivity

In a final step, we investigate the issue of complementarity or substitutability of the innovation modes for productivity (ex-post complementarity/substitutability). To this end we estimate an augmented (labor) productivity equation:

$$LP_{ft} = [\sum_{i,j,k} \varphi_{i,j,k} I(y_{f,1,t} = i, y_{f,2,t} = j, y_{f,3,t} = k)] + \theta' Z_{f,t} + \omega_{f,t}, \qquad (4)$$

with the first term on the RHS of (4) a short-cut for a set of innovation dummies and Z_{ft} a set of control variables. This set includes a measure for the capital intensity of firms, employment for labor inputs, a constant term and a set of dummies to control for industry - and time effects on firm-level productivity and $\omega_{f,t}$ a disturbance term. Equation (4) directly refers to firm-level data. When using DMD the firm index f represents the combination of e-business profiles, countries and industries in a given year t.

In (4) $I(0,0,0)$ is used as a reference category. Thus, for N = 3 there are seven dummies reflecting the contributions of different combinations of ES adoption (0,0,1), (0,1,0), (0,1,1), …, (1,1,1) to LP and compared to the contribution of $I(0,0,0)$, i.e. their contribution compared to not adopting any ES mode at all. These ES adoption values are latent and endogenous. Thus, one may expect that the OLS-estimates of (4) are contaminated by a simultaneity bias. To investigate this problem we used an instrumental variable estimation method to obtain an unbiased assessment of their ex-post contribution to LP (see e.g. Wooldridge, 2002). We re-estimated the productivity equation by the General Method of Moments (GMM). See section 5.2. for further details.

3.3 Testing ex-post complementarity or substitutability for productivity

The estimates of the augmented production function (4) do not allow us to draw final conclusions on the complementarity or substitutability of ES modes for productivty. This is because all estimates are relative to the reference (the combination $I(0,0,0)$). A more complete picture can be obtained by applying the so-called Kodde-Palm test (Kodde-Palm, 1986) used in Mohnen-Röller (2005). The test statistic can be calculated after re-estimating the (GMM) models using all ES dummies (thus including the reference category, and dropping the constant term), and by capturing the coefficient estimates and their covariances to solve a set of quadratic minimization problems under inequality constraints. The test statistics is given by

$$D = (S\tilde{\varphi}_{IV} - S\tilde{\varphi}_{IV})'(S'cov(\tilde{\varphi}_{IV})S)^{-1}(S\tilde{\varphi}_{IV} - S\tilde{\varphi}_{IV}) \tag{5}$$

with $\tilde{\varphi}_{IV}$ a vector with Instrumental Variable estimates (in our case GMM) for the profile dummies in (4) and cov($\tilde{\varphi}_{IV}$) the corresponding estimated covariance matrix. The matrix S maps the coefficients of the innovation dummies included in $\tilde{\varphi}_{IV}$ into the relevant constraints. For example, if we are testing complementarity between ERP and CRM systems for productivity it can verified that S in (5) takes the form

$$S = \begin{bmatrix} -1 & 0 & 1 & 0 & 1 & 0 & -1 & 0 \\ 0 & -1 & 0 & 1 & 0 & 1 & 0 & -1 \end{bmatrix}$$

See also Polder et al. (2010).

4. Data

4.1. The dataset

The data used in the DMD models are sourced from the V34-version of the ESS-Limit cross-country-industry database.[4] In particular, we make use of the ECSTAT and PSSTAT modules, which contain the profile averages (under subname

[4] See Hagsten et al. (2012) and the project website www.esslimit.eu for more information on the dataset.

‘BUSORG’) and the number of observations used in constructing the pertinent averages. This micro-aggregated database is the result of work carried out by the 15 participating NSIs, starting from their firm-level source data (in this case the ICT survey and production statistics). Table 1 shows the distribution of firms over the different profiles by country. Tables 2a shows the mean values and standard deviations by e-business profile used in the modelling exercise for the DMD data and Table 2b shows the corresponding results for the Dutch firm-level data. Note that the descriptive statistics for DMD are calculated using (employment weighted) industry -, country - and year averages and that the corresponding descriptive statistics for the Dutch firm-level data are calculated over firms, industries and years with no weighing applied.

Table 1. Number of observations for e-business profiles (ERP, CRM, SCM) by country, 2007-2009.

Country	**111**	**110**	**101**	**100**	**011**	**010**	**001**	**000**	**total**
AT	1,958	3,609	466	1,620	710	3,652	579	5,937	18,531
DE	3,136	4,853	987	2,077	582	3,017	413	5204	20,269
DK	1,915	4,152	660	2,909	660	2,005	967	8,510	21,778
FI	2,526	2,210	1,030	1,549	1,230	2,181	1,604	6,732	19,062
FR	3,393	5,087	3,230	9,182	1,069	3,177	2,581	22,582	50,301
IE	375	952	195	857	168	1,273	223	4,910	14,359
IT	10,134	12,958	5,754	12,592	8,020	15,558	15,074	68,182	148,272
LU	316	613	88	384	262	856	421	4,460	11,784
NL	1,943	4,032	1,160	3,366	574	2,978	663	8,022	22,738
NO	1,381	2,537	448	1,290	1,569	4,440	1,556	9,601	22,822
PL	3,599	5,413	1,620	3,379	2,114	6,462	3,479	32,420	58,486
RO	2,826	5,751	931	3,572	964	3,630	3,023	40,068	60,765
SE	3,205	2,513	1,123	1,360	1,212	1,844	1,438	6007	18,702
SI	343	677	345	910	161	352	1,064	5,682	9,534
UK	1,306	1,281	681	1,594	544	2,332	374	4,730	12,842

Table 2a. Descriptive statistics by e-business profile for DMD data, 2007-2009.

					DTF country	
profile	broadpct	e-purchpct	e-salespct	ERP	CRM	SCM
111	0.532	0.205	0.226	0.718	0.724	0.590
	(0.227)	(0.163)	(0.185)	(0.215)	(0.179)	(0.267)
110	0.495	0.092	0.120	0.704	0.713	0.551
	(0.213)	(0.094)	(0.150)	(0.235)	(0.185)	(0.290)
101	0.466	0.170	0.246	0.761	0.722	0.623
	(0.229)	(0.164)	(0.238)	(0.194)	(0.182)	(0.260)
100	0.415	0.071	0.108	0.719	0.711	0.568
	(0.198)	(0.081)	(0.160)	(0.221)	(0.184)	(0.281)
011	0.509	0.153	0.169	0.697	0.720	0.574
	(0.273)	(0.177)	(0.196)	(0.221)	(0.177)	(0.266)
010	0.473	0.087	0.101	0.683	0.705	0.540
	(0.230)	(0.107)	(0.137)	(0.236)	(0.188)	(0.286)
001	0.377	0.121	0.166	0.704	0.704	0.570
	(0.230)	(0.143)	(0.199)	(0.228)	(0.189)	(0.272)
000	0.339	0.057	0.082	0.696	0.706	0.548
	(0.178)	(0.073)	(0.129)	(0.239)	(0.190)	(0.290)

Means and standard deviations (in parenthesis) for “average firms” used in adoption model.

Table 2b: Descriptive statistics by e-business profile for Dutch firm-level data.

					DTF country	
Profile	broadpc t	e-purchpct	e-salespct	ERP	CRM	SCM
111	0.620	0.208	0.091	0.597	0.622	0.478
	(0.321)	(0.301)	(0.195)	(0.160)	(0.220)	(0.120)
110	0.591	0.110	0.046	0.622	0.685	0.477
	(0.327)	(0.203)	(0.135)	(0.153)	(0.207)	(0.117)
101	0.460	0.114	0.074	0.616	0.565	0.498
	(0.298)	(0.207)	(0.179)	(0.177)	(0.171)	(0.145)
100	0.476	0.087	0.043	0.634	0.642	0.479
	(0.307)	(0.190)	(0.139)	(0.168)	(0.200)	(0.118)
011	0.675	0.176	0.121	0.554	0.685	0.493
	(0.332)	(0.239)	(0.211)	(0.136)	(0.269)	(0.094)
010	0.736	0.137	0.061	0.576	0.788	0.476
	(0.353)	(0.217)	(0.150)	(0.104)	(0.219)	(0.079)
001	0.476	0.153	0.125	0.532	0.599	0.484
	(0.353)	(0.240)	(0.247)	(0.133)	(0.248)	(0.120)
000	0.468	0.124	0.068	0.590	0.677	0.488
	(0.379)	(0.221)	(0.172)	(0.151)	(0.225)	(0.116)

Means and standard deviations (in parenthesis) calculated for firms used in adoption models.
Calculations based on one-year lagged values.

4.2. Variables

In this section we discuss the variables that are used in this research. The explanatory variables chosen for estimating the adoption model (1b) refer to ICT readiness or, better, ICT maturity, and the relative importance of e-sales and e-procurement (e-purchasing) of firms. A natural candidate for ICT readiness (maturity) when looking at e-business processes is the intensity of broadband usage (cf. Eurostat, 2008). We conjecture that ICT maturity is a prerequisite for bringing forward ICT-enabled organization in the form of implementing ES systems and that broadband connectivity is a useful metric for capturing this. That's why we employ the share of broadband-enabled personnel in total employment as our measure of ICT readiness/maturity. This measure is derived by multiplying the availability of broadband connections (a binary measure) with the share of employees that has access to the internet (a continuous measure).

In addition the (continuous) shares of e-sales in total sales and of e-purchases in total purchases of firms are directly available from the surveys used. Because these variables are more or less directly linked to ICT related externalities, and many functionalities of ES systems aim at covering external links implicit in e-commerce practices, we consider these variables as useful predictors for the adoption of ES systems. Furthermore, and to account for size dependence of adoption, we also include size dummies when estimating (1b).

For the estimations based on firm-level data, the above mentioned variables are readily available in the ICT usage survey and are fully harmonized across countries and industries. Using cross-country-industry data for the different e-business profiles from DMD, however, requires DMD to construct averages for every e-business profile and for every combination of country, industry and year. To achieve this every firm is assigned to one of the eight profiles and according to the implementation/adoption of different combinations of ES. In general, this classification considers observations where ERP = a, CRM = b, and SCM = c (a, b, and $c \in \{0,1\}$) in industry s and country l and in year t. Then we can use the firm level x's to construct the following explanatory variables for using DMD data for the estimations:

$$(\bar{x})_{l,s,t}^{a,b,c} = \sum_{f \in \{l,s,t\}} \frac{e_{f,l,s,t,}}{\sum e_{f,l,s,t}} x_{f,l,s,t} 1(ERP = a, CRM = b, SCM = c)$$

with $e_{f,l,s,t} / \sum e_{f,l,s,t}$ the employment based weights used for the construction of profile averages. In addition, learning effects are taken into account as the relative difference with the 'frontier' for the percentage of usage of a particular e-business system y_i in a country. The distance to the country-frontier is implemented by calculating the quotient of the (employment weighted) industry averages and the maximum of these averages over countries in a particular year t for DMD data[5]:

$$DTF\left(y_{i,lst}\right) = \frac{\bar{y}_{i,lst}}{\max(\bar{y}_{i,lst})}.$$

When using Dutch micro data, we use the maximum for the percentage usage of e-business systems over industries in a particular year,

$$DTF\left(y_{i,st}\right) = \frac{\bar{y}_{i,st}}{\max(\bar{y}_{i,st})}.$$

The x variables by e-business profile are readily available from the cross-county dataset in the ESSLimit project; the *DTF* variables are calculated on the basis of the cross-country-industry data on y_i for DMD, after first aggregating the firm-level binary responses by industry (i.e. constructing average adoption intensities). The former variables relate the adoption of e-business systems to the usage of fast internet and a firm's strategy with respect to automizing its procurement and sales. The latter variables relate the adoption to a learning effect, which is defined as a potential "spillover" from the industry that is the most-intensive user of a particular system. To mitigate problems of reverse causality and endogeneity, all explanatory variables are lagged when using plain firm-level data for the Netherlands. However, constructing lags for the DMD data is virtually impossible. Because of a lack of panel design in the collection of the data, every combination of e-business profile, industry and country may consist of a completely different set of firms in adjacent years. This makes it impossible to construct lagged variables for adoption practices that are referring to the same underlying (set of) firms. For this reason we use contemporaneous observations only in the DMD based part of the empirical estimation.

A comparison of the results presented in tables 2a and 2b show some interesting differences between the two types of data. Firstly, and at first glance, there seems to exist a positive correlation between ES adoption and fast internet usage and e-commerce practices. Not, surprisingly the difference is more marked when compar-

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[5] Because the basic measurement is binary, the only way to account for learning or catching up effects is to aggregate first the firm responses to the industry level.

ing no adoption (0,0,0) with full adoption (1,1,1). Secondly, and in particular for fast internet usage and the e-commerce variables, the dispersion in the data is smaller when using firm-averages compared to using plain micro data. Lastly, the DTF measures show that the catching up potential is largest for SCM: the averages are smaller than for ERP and CRM.

5. Discussion of results

The main focus in this paper is on the comparison of firm-level micro data and DMD use, both for analyzing ES adoption decisions of firms and the consequences of these decisions for (productivity) performance. This is dealt with by making the best use of DMD for constructing a research setup that resembles micro data level based research. In terms of data construction, this exercise is more straightforward for the micro data, than for the micro-aggregated data in the cross-country-industry dataset.

For each country/industry/year combination, we have an 'observation' for each of the eight profiles (according to whether a firm has available an ERP, CRM and/or SCM system), which translates into observations of ERP, CRM and SCM. These are used as the dependent variables for the multivariate probit analysis. Moreover, in the cross-country dataset we have available (employment weighted) averages for several variables by e-business profile (see table 2a). These can be used as explanatory variables in the multivariate probit. In addition, country and industry specific variables can be taken or constructed from the cross-country dataset, and used as additional explanatory variables.

5.1 ES adoption decisions

We first comment on the results for ES adoption. To save space we will not discuss all available estimates, but focus on the marginal effects that can be derived from the MVP models and only for the most encompassing model, i.e. the model that includes the estimation of possible complementarities between or substitutability of adopting combinations of ES. Table 3 presents the marginal effects for the so-called "Lewbel model" for the two types of data for the adoption of three ES modes: 1) Enterprise Resource Planning (ERP), 2) Customer Resource Planning (CRM) and 3) Supply Change Management (SCM). The DMD results are obtained for the period 2007-2009, for which most countries have these data available. The micro-data results refer to the same period.[6]

[6] We recall that the measurement of ES is a relatively new phenomenon in the ICT usage survey, due to which the period of analysis is relatively short.

Table 3: Comparing marginal effects (ME) Lewbel adoption model for DMD data (N = 2626) and firm-level data for the Netherlands (Micro, N = 4195)

	ES system	ERP		CRM		SCM	
	Variables	ME	se	ME	se	ME	se
DMD	Share of broadband enabled employees t	0.599 ***	0.071	0.589 ***	0.043	0.054 ***	0.015
	Share of e-purchasing in total purchases t	0.224 **	0.107	0.239 ***	0.064	0.887 ***	0.064
	Share of e-sales in total sales t	0.280 ***	0.082	0.064 *	0.034	0.489 ***	0.041
	log(distance to country frontier) t	-0.012	0.042	-0.027	0.023	0.020 *	0.012
	Size dummies included	yes		yes		yes	
	ρ21	-0.056					
	ρ31	-0.091					
	ρ32	-0.039					
	complementarity/subtitutability ERP/CRM	-0.346 ***	0.049	-0.346 ***	0.049		
	complementarity/subtitutability ERP/SCM	-0.286 ***	0.018			-0.286 ***	0.018
	complementarity/subtitutability CRM/SCM			-0.103 ***	0.016	-0.103 ***	0.016
Micro	Share of broadband enabled employees t-1	0.104 ***	0.027	0.225 ***	0.018	0.049 **	0.021
	Share of e-purchasing in total purchases t-1	0.035	0.037	0.071 ***	0.026	0.187 ***	0.028
	Share of e-sales in total sales t-1	0.099 **	0.050	-0.028	0.032	0.143 ***	0.041
	log(distance to country frontier) t-1	0.107	0.074	0.068	0.037	0.027	0.054
	Size dummies included	yes		yes		yes	
	ρ21	0.076					
	ρ31	0.066					
	ρ32	0.068					
	complementarity/subtitutability ERP/CRM	0.287 ***	0.034	0.287 ***	0.034		
	complementarity/subtitutability ERP/SCM	0.194 ***	0.045			0.194 ***	0.045
	complementarity/subtitutability CRM/SCM			0.078 ***	0.022	0.078 ***	0.022

Table notes: period 2007-2009. Estimation by Simulated Maximum Likelihood. DMD results are based on micro-aggregated-data from the ESSLimit Cross-Country-Industry database. The ρ parameters are calculated from the generalized residuals of the probit equations (see Gourieroux et al.,1987). All models use industry and time dummies. DMD also uses country dummies. The value of the Likelihood function is -5443.1 for DMD and -8698.6 for Micro. *, ** and *** denote statistical significance at the 10%, 5% and 1% level respectively.

We see that the probability of adopting a certain ES type increases with the intensity of fast internet usage. This result is obtained both for DMD and the plain micro data for the Netherlands. Thus, the availability and penetration within the firm of fast internet can be thought to increase the value of adoption of these types of e-business.

The results for the two e-commerce predictors are less clear cut. The extent to which a firm has engaged in e-commerce increases the probability of adoption for all types of e-business in DMD, although e-sales is only weakly significant for CRM adoption. However, in the micro data we find that e-purchasing for ERP and (surprisingly) e-sales for CRM are not significantly different from zero. For SCM, the results for the e-commerce variables are more robust, with the contribution of these variables to the probability of adopting positive in the DMD results, as well as in the results based on plain micro data.

Looking next at the results for the DTF measures, the results are insignificant in general. This disappointing result may be due to the crude measures used in the empirical application.[7] Moreover, a broad view on all results, leads to the conclusion that the economic significance is somewhat higher for DMD than after using plain firm-level data. There may be several issues at stake here. Firstly, DMD may be less vulnerable for unobserved heterogeneity e.g. caused by the unobserved contribution of other innovation strategies hidden in the equation errors and that can be captured more conveniently by industry and country dummies in DMD. Secondly, the averaging over firms may pay out in the form of reducing the influence of measurement or, stated otherwise, in the form of improving the signal-noise ratio of the data. The method of weighing may also play a role. We used employment weighted averages in DMD to account for the presumption that larger firms get more attention in the process of constructing aggregates. Indeed, we found a strong positive size dependency on ES adoption (not shown in table 3) for DMD as well as after using micro data.

A striking difference between the two approaches concerns the estimates for the complementarity/substitutability parameters of the models. After controlling for the correlations between the equation errors, the estimates clearly point to substitutability in case of using DMD. By contrast, the results after using plain micro data lead to the conclusion the ES types are complements. This diverging pattern of results holds for every combination of ES types. A possible reason for this diverging result, and that deserves further investigation, is that unobserved heterogeneity may be cancelled out in DMD, whereas it is more difficult to control for unobserved heterogeneity when using plain micro data.

In the next part of the paper, we elaborate on the issue of joint adoption of e-business systems when assessing the contribution of different combinations of ES systems to productivity.

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[7] One reason is that these measures are derived from binary indicators.

5.2 Impact of ES adoption on productivity

This section discusses the productivity impact of applying different types of ES modes. It is possible to estimate a productivity equation also by DMD, using productivity averages by e-business profiles from the ESSLimit database, along the same lines as for the adoption models. Using average labour productivity by profile as the dependent variable, we can use

$$(\overline{va/emp})_{lst}^{p} = \alpha + \gamma_p \sum_p I(profile = p) + \beta_1 (\overline{k/emp})_{lst}^{p} + \beta_2 (\overline{emp})_{lst}^{p} + \varepsilon_{lst}$$

where *va*/*emp* is labour productivity measured by value added over employment, *emp* is employment, and k/emp is capital stock (proxied by depreciation) per employee, and ε is a disturbance (all variables are expressed in logarithms). Finally, *I*(*profile* = *p*) are dummies for the adoption profiles, where *p* = {(0,0,1), (0,1,0),…, (1,1,1)}. Note that *p* = (0,0,0) is used as a reference category.

Results for different productivity regressions are given in table 4. The baseline model uses OLS with dummies for the ES profiles added to the traditional inputs. In addition, and to control for the robustness of the OLS results for endogeneity of the ES innovation dummies, we apply GMM as an instrumental variable method, with the e-business dummies instrumented with the predicted propensities of the adoption model, as suggested by Wooldridge (2002). The set of instruments is extended with lagged values for the capital intensities, employment (both in logs), the broadband intensity indicator and an e-commerce intensity indicator (the share of electronic sales in total sales plus the share of electronic purchases in total purchases). For DMD the lags are constructed using data on the country-industry-year level. In both methods we use cluster fixed effects in estimating the standard errors for DMD data.

The most interesting part of table 4 concerns the contribution of ES adoption to productivity. The general picture is that adoption of ES increases productivity, and that the joint adoption of ES types pays off. The pattern of estimates show that joint adoption is more profitable than adopting a single ES type (an exception is the profile (0,1,0) for DMD-GMM). In particular the ES combinations which involve ERP are most productive. This result mirrors that ERP can be seen as a back-bone for other types of ES.

Another interesting result is that controlling for the endogeneity of ES-dummies by applying GMM makes a difference in the sense that the economic significance of the estimates improve considerably. Moreover, and similar to the results presented in table 3, it appears that the estimates are more robust and economically significant if we use firm-averages and compared to using plain micro data. Thus, the conclusion drawn for the adoption models that DMD mitigates problems of measurement error and unobserved heterogeneity carries over to the productivity regressions.

Table 4: Productivity regressions (dependent variable is log(*Y*/*L*))

	DMD						MICRO					
Method	OLS			GMM			OLS			GMM		
Variables	coeff.		se	coeff.		se	coeff.		se	coeff.		se
log(*K*/*L*)	0.223	***	0.016	0.183	***	0.019	0.247	***	0.006	0.207	***	0.030
log(*L*)	-0.044	**	0.017	-0.204	***	0.035	0.047	***	0.007	-0.146	***	0.062
I(001)	0.100	***	0.036	0.115		0.139	0.039		0.050	-2.981		1.874
I(010)	0.099	***	0.024	0.386	**	0.174	0.107	***	0.028	1.293		0.933
I(011)	0.183	***	0.034	0.220		0.196	0.026		0.051	-2.266		2.163
I(100)	0.165	***	0.028	0.539	***	0.139	0.108	***	0.026	0.929		0.749
I(101)	0.278	***	0.046	0.529	***	0.111	0.118	***	0.035	2.715	***	1.011
I(110)	0.279	***	0.036	1.025	***	0.134	0.133	***	0.024	0.805	*	0.498
I(111)	0.394	***	0.042	1.020	***	0.145	0.231	***	0.031	1.606	***	0.695
constant	3.754	***	0.081	1.005	***	0.267	3.732	***	0.044	3.470	***	0.220
Dummies:												
year	yes			yes			yes			Yes		
industry	yes			yes			yes			Yes		
country	yes			yes								
R^2	0.982						0.283					
J-statistic (*p*-val)				0.145						0.130		
N	1805			1640			5164			3402		

Instruments for GMM: predicted propensities d001-d111, log(K/L) t-1, log(L) t-1, broadband intensity t-1, ecompct t-1 (ecompct is the sum of the share of e-sales and e-purchases). DMD models use robust clustering for the standard errors of the estimates. *, ** and *** denote statistical significance at the 10%, 5% and 1% respectively.

Table 5: Results for testing super and sub modularity using the LP equation

I) H0: complementarity			
Combination	ERP/CRM	ERP/SCM	CRM/SCM
KP test statistics DMD	8,16	1,15E-5	0,319
KP test statistics MICRO	1,66	1,01E-7	0,154
II) H0: substitutability			
Combination	ERP/CRM	ERP/SCM	CRM/SCM
KP test statistics DMD	1,48E-11	8,253	0,162
KP test statistics MICRO	0,091	9,677	1,053

The lower bound for the Kodde-Palm (KP) test for 2 degrees of freedom is 1.642 at 5% level of significance and 3.808 at 10% level of significance. The respective upper bounds are 2.706 and 5.138.
The null-hypothesis is accepted if the test statistics falls below the lower bound and is rejected if it falls above the upper bound. In between the two bounds the test is inconclusive.

5.3 Results of the Kodde-Palm test for complementarity and substitutability

The estimates of the ES dummies in table 4 do not provide a complete story on the complementarity or substitutability of adoption modes in raising productivity. This is because all estimates are relative to the reference (the combination d000). A more complete picture can be obtained by testing the inequality conditions derived in section 3.3. The Kodde-Palm (1986) test statistic used in the Mohnen-Röller (2005) test procedure can be calculated by re-estimating the GMM models using all ES dummies and by capturing the estimates and their covariances to solve the set of quadratic minimization problems under inequality constraints given in (5).

The tests of complementarity and substitutability of ES modes in terms of productivity presented in table 5 clearly show that ERP and SCM are strong complements: the test statistics reveal that the null hypothesis of complementarity is convincingly accepted and that of substitutability is strongly rejected. The opposite result is obtained for the ERP/CRM combination. Here we find strong evidence that ERP and CRM are substitutes, a result that can be understood taking into account that ERP is a more encompassing type of ES than CRM. Somewhat surprisingly, the results for the combination of CRM and SCM are contradictory, with the tests accepting both the null hypothesis of complementarity and substitutability.

6. Conclusion

We have investigated the adoption and productivity effects of Enterprise Systems, focussing on Enterprise Resource Planning, Customer Relation Management, and Supply Chain Management. With an eye on the possible complementarity between different Enterprise Systems, we look at the possible simultaneity and cross-dependence between the adoption decisions, and moreover at the productivity effects of different combinations of these systems.

These research questions are addressed by relying on two types of data. We compare the results of using plain micro data for the Netherland with results obtained after using firm-averages constructed by DMD. Despite the short period that can be covered and the differences in nature of the data, we obtain some interesting common results.

We find that fast internet increases the probabilities of adoption and that the extent to which a firm has engaged in e-commerce also increases the overall value of adopting e-business practices.

With respect to productivity effects we find that, in our most advanced and preferred model, combinations that do not involve the adoption of ERP do contribute less when explaining differences in productivity. Hence, ERP appears to be a prerequisite for the success of other Enterprise Systems. This corroborates with the results of Aral et al. (2006) and the conclusion of Zand (2011), that ERP can be seen as the most important instance of ICT enabled organizational change to increase business value.

An important methodological implication of this research is that it shows that, by cleverly constructing moments from the micro-data, the cross-country micro-aggregated data can be used to estimate ‘pseudo-micro-data’ regressions. DMD data even appears to be a feasible alternative for plain firm-level data when it comes to the estimation of more complex models that feature new directions in micro-econometrics.

Besides the advantage of pooling country-data, this also has a major advantage because of the fact that (non-systematic) measurement errors are wiped out, so that estimates are expected to be less biased. The higher economic significance of the DMD estimates clearly points to the importance of this issue.

Of course, the other side of the coin is that it is more difficult to control for unobserved heterogeneity at the firm-level, and one is less flexible with the implementation of different estimation methodologies, which require different moments from the data to be collected. However, given that the ESSLimit project has achieved the availability of a harmonized metadata structure over countries concerning the underlying micro datasets, it should be possible to easily gather these additional micro-moments in the future. We view this as a fruitful and exciting extension of the DMD approach as it exists today.

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Appendix A. The likelihood function for the Lewbel Model

In this appendix we describe the derivation of the likelihood function for our empirical application. The computational complexities arise due to the requirement to have full error support over all possible combinations (strategy choices). Referring to equations (2) in the text, there are eight possible combinations of the three types of innovation. Thus, for every adopted combination, $2^N - 1 = 7$ comparisons are at stake. To keep things tractable we will focus on strategy (2a). Adopting strategy (2a), no adoption at all (thus all comparisons are against zero profits), yields the following set of inequalities[8]:

$$
\begin{aligned}
&V(0,0,0) \Leftrightarrow V(0,0,1) \Rightarrow \varepsilon_3 < -\beta_3' x_3 = UB_3 \equiv UB_3^d \\
&V(0,0,0) \Leftrightarrow V(0,1,0) \Rightarrow \varepsilon_2 < -\beta_2' x_2 = UB_{21} \equiv UB_{21}^d \\
&V(0,0,0) \Leftrightarrow V(0,1,1) \Rightarrow \varepsilon_2 < -\beta_2' x_2 - \beta_3' x_3 - \alpha^{23} - \varepsilon_3 = UB_{22} \equiv UB_{22}^d - \varepsilon_3 \\
&V(0,0,0) \Leftrightarrow V(1,0,0) \Rightarrow \varepsilon_1 < -\beta_1' x_1 = UB_{11} \equiv UB_{11}^d \qquad\qquad \text{(A1)} \\
&V(0,0,0) \Leftrightarrow V(1,1,0) \Rightarrow \varepsilon_1 < -\beta_1' x_1 - \beta_2' x_2 - \alpha^{12} - \varepsilon_2 = UB_{12} \equiv UB_{12}^d - \varepsilon_2 \\
&V(0,0,0) \Leftrightarrow V(1,0,1) \Rightarrow \varepsilon_1 < -\beta_1' x_1 - \beta_3' x_3 - \alpha^{13} - \varepsilon_3 = UB_{13} \equiv UB_{13}^d - \varepsilon_3 \\
&V(0,0,0) \Leftrightarrow V(1,1,1) \Rightarrow \varepsilon_1 < -\beta_1' x_1 - \beta_2' x_2 - \beta_3' x_3 - \alpha^{12} - \alpha^{13} - \alpha^{23} \\
&\qquad - \varepsilon_2 - \varepsilon_3 = UB_{14} \equiv UB_{14}^d - \varepsilon_2 - \varepsilon_3
\end{aligned}
$$

In (A1) we make a distinction between the deterministic part (indicated by UB_{ij}^d) and the stochastic part of the right-hand side (RHS). Notice that, for $N = 3$, we have one inequality involving ε_3, two involving ε_2 and four involving ε_1. Any coherency problem is lifted if we take the minimum of the upper bounds of the inequalities on the right-hand sides.

So we replace the inequalities for ε_2 by

$$\varepsilon_2 < \min(UB_{21}^d, UB_{22}^d - \varepsilon_3)$$

and similarly for the inequalities involving ε_2

$$\varepsilon_1 < \min(UB_{11}^d, UB_{12}^d - \varepsilon_2, UB_{13}^d - \varepsilon_3, UB_{14}^d - \varepsilon_2 - \varepsilon_3 \;.$$

The (joint) probability for the case of no adoption at all is given by

$$
\begin{aligned}
&\Pr\{ y_1 = 0, y_2 = 0, y_3 = 0\} \\
&\qquad = \Pr\{ \varepsilon_1 < \min(UB_{11}^d, UB_{12}^d - \varepsilon_2, UB_{13}^d - \varepsilon_3, UB_{14}^d - \varepsilon_2 - \varepsilon_3) \\
&\qquad \& \ \varepsilon_2 < \min(UB_{21}^d, UB_{22}^d - \varepsilon_3) \ \& \ \varepsilon_3 < UB_3^d \}
\end{aligned}
$$

---

[8] We use superscripts to denote the sum of α_{ij} and α_{ji}. Thus, $\alpha^{ij} = \alpha_{ij} + \alpha_{ji}$.

$$= \Pr\{ \varepsilon_1 < \min(UB_{11}^d, UB_{12}^d - \varepsilon_2, UB_{13}^d - \varepsilon_3, UB_{14}^d - \varepsilon_2 - \varepsilon_3)$$

$$| \varepsilon_2 < \min(UB_{21}^d, UB_{22}^d - \varepsilon_3) \; \& \; \varepsilon_3 < UB_3^d \}$$

$$\times \Pr\{ \varepsilon_2 < \min(UB_{21}^d, UB_{22}^d - \varepsilon_3) \mid \varepsilon_3 < UB_3^d \}$$

$$\times \Pr\{ \varepsilon_3 < UB_3^d \} .$$

Similar expressions can be derived for the other combinations of strategies. The expressions involve conditioning upon unobservable variables to enable GHK simulation for evaluating the integration bounds in the likelihood function. For example for P(0,0,0), the likelihood function is given by

$$\int_{-\infty}^{UB_3^d} f(\varepsilon_3) d\varepsilon_3 \times \int_{-\infty}^{\min\{(UB_{21}^d, UB_{22}^d - \varepsilon_3) | \varepsilon_3\}} f(\varepsilon_2 | \varepsilon_3) d\varepsilon_2$$

$$\times \int_{-\infty}^{\min\{(UB_{11}^d, UB_{12}^d - \varepsilon_2, UB_{13}^d - \varepsilon_3,, UB_{14}^d - \varepsilon_2 - \varepsilon_3) | \varepsilon_2, \varepsilon_3\}} f(\varepsilon_1 | \varepsilon_2, \varepsilon_3) d\varepsilon_1$$

where *f* stands for the density function of the normal distribution.