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Determination of the Threshold in Cutoff Sampling Using Response Burden with an Application to Intrastat

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Statistical offices frequently use cutoff sampling to determine which businesses in a population should be surveyed. Examples include business surveys about international trade, production, innovation, ICT usage and so on. Cutoff thresholds are typically set in terms of key variables of interest and aim to satisfy a minimum coverage ratio–the share of aggregate values of reporting units. In this article we propose a simple cost-benefit approach to determination of the sampling cutoff by taking into account the response burden. In line with existing practice, we use the coverage ratio as our measure of accuracy and provide either analytical or numerical solutions to cutoff determination. Using a business survey on response burden of reporting trade flows within the EU (Intrastat), we present an application that illustrates our approach to cutoff determination. An important practical implication is the possibility to set industry-contingent cutoffs.

Key words: Accuracy; cost-benefit analysis; reporting costs; social benefits; social welfare function.

1. Introduction

As long ago as 1978, Bradburn (Bradburn 1978) raised the issue of "respondent burden" because of an increasing 'number and complexity of sample surveys'. Since then, burden has grown into an even more urgent matter, especially in business surveys, as with global competition, pressures on achieving higher productivity and the spread of lean approaches to eliminate any 'waste' activity, working time has become more precious and the opportunity cost of survey response higher. Businesses have been loudly questioning the need to provide data to the government, which has contributed to programs of administrative burden reduction and increased attention to burden in mandatory business surveys. National statistical institutes (NSIs) have taken different measures to reduce response burden; some of them try to help businesses to carry the burden by providing guidance and improving processes and others try to reduce the burden by reducing sample

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sizes, numbers of questions, and so on (Bavdaž et al. 2015, Giesen et al. 2018). This article mainly focuses on this second approach, controlling burden through sample sizes.

Economic activity is typically concentrated, with a large proportion of activity in a few, large businesses, and a relatively small proportion amongst many small businesses. Moreover, the activity of small businesses is often strongly correlated with that of surveyed large businesses through vertical supply linkages. This makes it possible to completely disregard the business units with the smallest values (a take-none stratum, hereinafter *E*, for "excluded") at the cost of a small bias. This sampling procedure is known as cutoff sampling. The part of the population which is included may be completely enumerated (take-all, *C*, for "completely enumerated"), sampled (take-some, *S*, for "sampled"), or divided into different strata in which one of the preceding options is used. The reason for choosing cutoff sampling is mainly pragmatic, to substantially reduce the cost of the survey while only modestly decreasing accuracy (Knaub 2007). Research on cutoff sampling has been relatively scarce. Some studies have focused on decreasing the potential bias in estimation because of excluded units by using auxiliary information (e.g., Haziza et al. 2010; Guadarrama et al. 2020). Other studies have focused on establishing optimal thresholds between take-none, take-some and take-all strata (e.g., Benedetti et al. 2010). We found only one study, Lee and Shin (2016), that explicitly considers the cost of data collection, and that has a quite different context. It doesn't consider the burden imposed on businesses but rather the cost to the statistical agency; it optimises the trade-off in sample size between an expensive take-all stratum and a less expensive take-some stratum; and it does not include a take-none stratum. Indeed, Lee and Shin (2016)'s optimisation uses variance estimates which do not exist in a take-none stratum.

Besides reducing the cost on the NSI side, another advantage of cutoff sampling is the reduction of response burden, typically among the smallest units that are most sensitive to it. To give some examples where cutoff sampling is used in the European Statistical System: the Prodcom Regulation states that NSIs are not required to survey enterprises with fewer than 20 employees (Eurostat 2020d); the Labour Cost Survey typically includes units with at least ten employees (Eurostat 2020b); the population for the Community Innovation Survey consists of all enterprises with ten or more employees (Eurostat 2020c); the population for the survey on ICT usage in enterprises consists of enterprises with ten or more persons employed (Eurostat 2020a), and so on. These examples demonstrate two subtly different strategies–the first two conceptually cover the whole population of businesses but use a cutoff design, whereas the second two redefine the population of interest to exclude businesses below the cutoff (Dalén 2005).

In Intrastat, the system for collecting information and producing statistics on the trade in goods between Member States of the European Union, coverage of at least 93% of the total value of intra-EU imports, and 97% of the total value of intra-EU exports is prescribed by Regulations (EC) No 638/2004 and No 222/2009. EU Member States have to set the exemption threshold for Intrastat so that it satisfies the prescribed coverage. Thresholds are therefore country specific and may change annually (thresholds for 2017–2020 are given in the Annex of Eurostat 2021b). The required minimum coverage of intra-EU imports was reduced three times in the past because of the high response burden in what is the largest business survey in the EU. With the implementation of the so-called FRIBS (Framework Regulation Integrating Business Statistics) regulation (Commission Implementing Regulation (EU) 2020/1197, 2020), the production of import statistics will not be

regulated at the EU level any longer, while more data will have to be collected on intra-EU exports from units above the exemption threshold and exchanged confidentially with relevant NSIs of other EU Member States; that is, intra-EU trade flows may only be measured in one direction.

The cutoff value is set according to a detailed technical procedure that also takes into account nonresponse, fluctuations in economic activity and response burden (Eurostat 2021a, Sec. 5). Scenarios with different coverage rates (i.e., different exemption thresholds) for 2005 showed that the impact on response burden (measured by the number of providers of statistical information) varied considerably across the Member States (Eurostat 2007a). Compared to a census, the impact would be larger when reducing the coverage of exports than imports for most Member States, with some notable exceptions (e.g., Germany, Italy, Austria), while compared to the actual coverage rate, reducing the coverage of exports would be preferred to imports in even more scenarios. Reducing the coverage rates would primarily affect businesses that report trade flows for just a few products, as their number and percentage among reporting units would considerably decrease, and it would also lower the quality of data at disaggregated (product, country) levels (Eurostat 2007b).

Despite the detailed presentation of scenarios, the selection of a specific coverage rate (and consequently, the exemption threshold) appears to be experiential rather than theoretically founded. Our article aims to address this gap by offering a simple theory of cutoff determination built around two key concepts from official statistics, namely accuracy and response burden. The research exposes trade-offs that are implicit in the cutoff determination, thus contributing to an increased transparency that is also advocated by the European Statistics Code of Practice (Eurostat 2018). Unlike Lee and Shin (2016), our approach focuses on costs incurred by businesses and uses cost functions that allow both fixed and variable costs. Heterogeneity of costs across units is common in business surveys and it is also clearly present in the Intrastat data used for illustration.

Our research was inspired by Abowd and Schmutte (2019) who analyse the trade-off between two competing mandates of NSIs – ensuring sufficient accuracy and privacy protection of responding units – as a problem of resource allocation; a decrease in accuracy is required to increase privacy protection. They solve an optimization problem where the objective is a social welfare function that depends on both accuracy and privacy, while taking into account a transformation curve as a constraint. Cutoff determination addresses a similar trade-off: a decrease in accuracy is required to free businesses of response burden; to increase accuracy, businesses incur higher opportunity costs as productive time is lost on reporting. However, for a social welfare function, we would have to model social preferences defined over accuracy of official statistics as the public good, and over consumption (arising from output generated from resources not used for statistical reporting) as the private good. Even though the use of social welfare functions is recommended for an analysis of costs and benefits (Adler and Posner 1999; Adler 2019), this approach goes beyond the scope of this article. We therefore narrow down the problem to the comparison of benefits from accuracy and costs incurred by businesses, and treat them in the framework of a cost-benefit analysis. A cost-benefit analysis is a technique for making decisions based on enumeration and evaluation of all relevant (direct and indirect) costs and benefits (Prest and Turvey 1965; Layard and Gleister 1994). We will conduct a simple cost-benefit analysis given our focus just on the main (but most sensitive)

component of costs, and therefore disregard cost components such as privacy costs, or costs to NSIs of running the survey. Optimal levels of response burden and accuracy will be determined when the marginal cost of the additional response burden equals the marginal benefit of the additional accuracy.

The article continues in Section 2 with a discussion of related literature, and Section 3 proposes a theory of cutoff determination, which also includes the operationalisation of relevant concepts. Section 4 presents an empirical application using intra-EU trade data and Section 5 concludes with a discussion of the findings and some proposals for future research.

2. Related Literature

In this section we briefly discuss the literature that provides the two main building blocks for our proposed theory of cutoff determination. The first block is the theory of cutoff sampling and second is the cost-benefit analysis. We discuss these in turn.

2.1. Cutoff Design

The literature on designing cutoff samples is rather sparse even though they are widely used. It distinguishes between two cases – one where there are two strata, a take-all stratum (C) and a take-none stratum (E); and a second where there is additionally a take-some stratum (S). These two cases will be labelled EC and ESC respectively.

In EC designs, there is strictly no (design-based) sampling variance, whereas in ESC a sampling variance arises in the S stratum. E can be regarded as containing negligible activity, so that it may be ignored, or, more usually, a model based on some auxiliary information is used as the basis for estimation in E. Knaub (2007) suggests the use of the variance from the model (a model-based accuracy measure) as the variance component, and this can be applied in both EC and ESC designs as the basis of a variance component of (model-based) mean squared error (henceforth MSE).

The approaches to defining the cutoff values (the boundary(ies) of the strata) are then:

1. The cutoff is set according to a minimum coverage criterion (Yorgason et al. 2011), so that at least $x\%$ of the population is covered by responses (for Intrastat this percentage is prescribed by Regulations (EC) No 638/2004 and No 222/2009). The idea is to make the bias (from either neglecting E or using a modelled estimate for E) sufficiently small. But this is not solvable through a minimisation, since the bias is minimised when C covers the whole population. So cutoffs set in this way rely on judgement. For further approaches it is necessary to generate an expression for the MSE (either the design-based MSE in ESC or the model-based MSE in either EC or ESC), which is followed by:
2. Minimising the MSE analytically with respect to the stratum boundaries. This is the basis of the Lavallée and Hidiroglou (1988) approach, which aims to optimise the placement of the boundary between C and S (without considering E).
3. Minimising the MSE numerically with respect to the stratum boundaries. Benedetti et al. (2010) use simulated annealing for this purpose to deal with ESC designs with multiple auxiliary variables, and Bee et al. (2011) use simulated annealing for this purpose to deal with ESC designs with multiple auxiliary variables, and Bee et al.

(2011) use the same approach to the univariate case in longitudinal surveys, focusing on determining the sample size required to meet a fixed MSE for estimating a ratio, and for estimating a total in the presence of nonresponse. This kind of approach has been used more widely in stratified designs (see Smith and Yung (2023) for an overview), but needs to be adapted to cutoff sampling to include the bias from neglecting or modelling E in the MSE.

4. Chaudron and Carlier (2015) do a grid search over the stratum boundaries in an ESC design and then choose the smallest MSE, although their description is not comprehensive.

There are therefore rather few approaches to objective optimisation of the cutoff with a univariate predictor. In this article we consider an EC design, similar to Yorgason et al. (2011). However, instead of relying on judgement in determining the cutoff, we develop an objective approach based on the trade-off between the costs and benefits of response in the survey.

2.2. *Cost-Benefit Analysis*

The second building block of our approach is cost-benefit analysis (Prest and Turvey 1965; Layard and Gleister 1994), which allows cutoff determination without reliance on arbitrary judgment. The cost-benefit approach is in our view more general as it does not only focus on minimization of MSE (subject to some constraints), but instead on choosing accuracy that yields the highest net benefits. In order to be able to calculate such net benefits, Layard and Gleister (1994, 2) note: "we should be willing to assign numerical values to costs and benefits, and arrive at decisions by adding them up and accepting those projects whose benefits exceed their costs."

The overall government goal is to maximize the social welfare subject to constraints given by preferences, technology and resources. In line with this aim, the government should use the cost-benefit approach to decisions by measuring the costs and benefits of individual agents, and then aggregating them. In the context of surveying, the costs are born by: (1) taxpayers, who pay for surveys conducted by national statistical institutes and (2) responding firms, whereas the benefits from surveying are accrued by residents, either directly or indirectly through ownership of firms. The residents enjoy the benefits of better governance (better economic policies) that stem from research activities and improvements in general knowledge, such as understanding economic relationships (a form of public good) that may lead to higher economic growth, but also macroeconomic and microeconomic policies designed to alleviate the implications of various transitory economic shocks. According to the cost-benefit analysis principle (Layard and Gleister 1994) we should appropriately determine the relative values of costs and benefits, taking into account the time, risk and individual valuations of incomes (due to income differences marginal utilities or valuations vary). While the most convenient way of expressing these costs and benefits is in monetary terms, this is not necessary (Layard and Gleister 1994).

In our framework both costs and benefits of reporting increase with accuracy – defined as the coverage ratio – which in turn depends on the cutoff that determines units included (and excluded) from the survey (The coverage ratio reflects the bias component of accuracy from sampling, since there is no sampling variance in a cutoff design). The main

trade-off is between social benefits of accuracy and reporting costs of survey respondents. While in practice the costs and benefits may accrue in different time periods and may be uncertain, we assume these complications away, but allow for differences in income inequality that may generate decreasing marginal benefits of accuracy. The proposed approach is different from the existing statistical literature, which has usually considered the social cost of inaccuracy alone (Spencer 1985; Spencer and Moses 1990; Trottini and Fienberg 2002; Spencer and Seeskin 2015).

Our approach is also quite different from the analysis recently considered by Abowd and Schmutte (2019). Unlike our problem of maximization of net social benefits, they frame the sample determination as a social welfare maximization problem with a trade off between the accuracy of statistical outputs and the privacy of survey respondents. While we could formulate our problem as a social welfare optimization problem, with accuracy as the public good and consumption as the private good, the limited information on the parameters of social welfare functions makes this route impractical, so we do not pursue it here. The second important difference from Abowd and Schmutte (2019) is in the arguments of the social welfare function. While we consider the costs of reporting, they focus on the cost of privacy loss. Lastly, their measure of accuracy is the expected squared error loss, which allows the error between the published estimate and the true population value to be stochastic due to randomness in the data publication mechanism, whereas our measure is a simpler coverage ratio that is not random.

3. A Theory of Reporting Cutoff Determination

3.1. Theoretical Framework

For cutoff determination within the cost-benefit framework, we use the net social benefits function as the objective function. It depends on two elements: (1) the social benefits ($B(A)$) and (2) reporting costs of survey respondents ($C(A)$), both of which depend on accuracy (A). As these two components do not have the same measurement units, we use weights in the social benefits function that allow comparison between costs and benefits. Specifically, we assume the following functional form for net social benefits:

$$NSB(A) = B(A) - C(A) = \lambda_0 A^{\lambda_1} - C(A), \tag{1}$$

where $\lambda_0 > 0$ converts the measure of accuracy into monetary units like costs; its positive value implies that the marginal benefit of accuracy is positive. λ_1 determines the shape of the marginal benefits function. If $\lambda_1 = 1$, the marginal benefit of accuracy is constant, while if $\lambda_1 < 1$, the marginal benefit is decreasing with accuracy.

In this article, the measure of accuracy is defined in terms of the reporting variable (V) and depends (i.a.) on a reporting or exemption cutoff $\underline{V}$. In empirical illustration of our approach to cutoff determination, the reporting variables are firm-level values of Intra-EU exports and imports, and cutoffs are determined in terms of these variables. Values of exports and imports in our empirical example come from administrative sources, but from a preceding period; we assume a strong relationship to the reporting variable, but leave the challenge of explicitly accounting for this relationship for further research. We do not consider defining a cutoff on variables that are not on the frame.

We now assume that the reporting variable (V) is a random variable with a continuous distribution. Then aggregate accuracy is defined as the proportional coverage of the population quantity:

$$A(\underline{V}) = \frac{\int_{\underline{V}}^{V_{max}} V f(V) \mathrm{d}V}{\int_{V_{min}}^{V_{max}} V f(V) \mathrm{d}V} \tag{2}$$

where f denotes the probability density function of V, V_{min} and V_{max} denote the lower and upper bounds of the distribution, and $\underline{V}$ denotes the reporting cutoff (sometimes also known as the exemption cutoff). Note that V_{min} is non-negative for most reporting variables (e.g., employment, turnover, investment etc. all have a minimum value of zero).

What is the interpretation of our measure of accuracy and how is this measure related to the standard measure of mean squared error? To provide the answers to these questions, note that the numerator is a partial expectation, which can be expressed as a product of the conditional mean for reporting firms, $E(V|V \geq \underline{V})$, and the share of reporting firms, $F(V \geq \underline{V})$, whereas the denominator is the expected value of the reporting variable or unconditional mean, $E(V)$. (Note that the measure of accuracy pertains to the total quantity or aggregate, so both the numerator and denominator should be multiplied by the same mass of firms (denoted N), which cancels and is thus not shown.) Hence our measure of accuracy is a product of two components (1) a ratio between the conditional mean and the unconditional mean, which reflects the bias of the conditional expectation, and (2) the share of reporting firms. As the reporting cutoff typically exceeds the lowest values, the conditional mean exceeds the unconditional mean (the ratio is above 1), and the share of reporting firms is below 1, with the product assuming values below 1.

Our exposition is for the estimation of a total, but the accuracy measure (2) is also related to the quality of other statistics such as means or ratios, though in these cases the reduction in accuracy from increasing the threshold would often be smaller since these statistics implicitly compensate for the cutoff part of the population. Inasmuch as Equation (2) is a good reflection of the effect of changing coverage on the quality of the estimate, the same arguments can be used for other outputs.

As EC cutoff sampling does not feature any design-based variance for the estimates, the design-based root mean squared error (RMSE) for the aggregate value of V is just equal to the bias of the aggregate value and can be directly expressed as a function of accuracy:

$$RMSE = N(E(V|V \geq \underline{V})F(V \geq \underline{V})) = N\,E(\mathrm{V})(1-A(\underline{V})), \tag{3}$$

Moreover, the RMSE expressed relative to the aggregate value of V is just $1-A(\underline{V})$.

Next we turn to aggregate costs of reporting; these are defined as the following partial expectation of cost function:

$$C(\underline{V}) = N \int_{\underline{V}}^{V_{max}} c(V) f(V) dV \tag{4}$$

where unit-level reporting costs c are allowed to vary with the reported value. In line with discussion below regarding the normalization of the net social benefits function, the mass of firms, N will be normalized to 1.

The cutoff is then determined using optimization methods by maximizing the net social benefits function. The solution to this problem will generally depend on the specific assumptions regarding the continuity and functional form of the probability density function of the variable of interest $f(V)$, the functional form for the cost function $c(V)$, and the preference parameters. In this article we assume that all functions are twice continuously differentiable with respect to $\underline{V}$.

The solution to the optimisation of the net social benefits function depends on the following derivative

$$NSB'(\underline{V}) = B'(A(\underline{V}))A'(\underline{V}) - C'(\underline{V}),$$

which has both corner and interior solutions. Two corner solutions refer to situations where no units are in the sample (no survey) or all units are in the sample (a census). The first case arises when the marginal social benefit of reporting is negative even at the upper bound ($\lim_{\underline{V}\to V_{max}} NSB'(\underline{V}) < 0$), and a census is a solution when at the lower bound the marginal net social benefit is still positive ($\lim_{\underline{V}\to V_{min}} NSB'(\underline{V}) > 0$). While these two cases are clearly relevant, we focus on determining interior solutions for which $NSB'(\underline{V})$ is equal to zero.

3.2. *Cutoff Determination for Reporting Variables with Log-Normal Pdfs*

The optimal reporting cutoff from the first-order condition $NSB'(\underline{V}) = 0$ depends on (1) the functional forms for the pdf $f(V)$, the function that maps accuracy to social benefits $B(A)$ and the function for the costs of reporting $c(V)$, and (2) the specific values of the parameters for these functions. The purpose of this article is not to provide a wide range of theoretical results for different functional forms, but instead to derive results for functional forms which are commonly used in survey and economic analysis, and to apply these to the Intrastat reporting of Slovenian business units (see Section 4).

As our main theoretical case we assume a log-normally distributed random variable V (i.e., ln V is normally distributed). We motivate this assumption with empirical evidence on business revenues whose logarithms are often bell-shaped and may be reasonably approximated using this distribution (e.g., Cabral and Mata 2003; Head et al. 2014; Bee and Schiavo 2018; Fernandes et al. 2018). We also consider an alternative assumption of the Pareto distribution (in Appendix, Subsection 6.1) that is used in theoretical models of international trade with heterogeneous businesses (e.g., Melitz 2003) and also documented in empirical analysis of business size distributions for variables such as revenues and employment (e.g., Axtell 2001; Gabaix 2009). For the cost function we assume a loglinear functional form in this section and Appendix, Subsection 6.1. (e.g., Nerlove 1963; Christensen and Green 1976). Finally, for the function that links benefits to accuracy we consider a power function with either constant or decreasing marginal social benefits of accuracy. The constant marginal social benefits require that agents are both risk neutral and society features no inequity aversion, while either risk aversion or inequity aversion would imply declining marginal social benefits (Stern 1976). An alternative motivation for declining marginal benefit of accuracy may be declining value of information for policy makers (e.g., Bikhchandani and Mamer 2013).

Based on the assumption of normality for ln V with mean μ and variance σ^2, we can express accuracy given in Equation (2) as a function of the reporting cutoff:

$$A(\underline{V}) = \frac{\frac{1}{\sqrt{2\sigma}} \int_{\underline{V}}^{V_{max}} e^{\ln V} e^{-\frac{1}{2}(h(\underline{V}))^2} \mathrm{d}V}{\frac{1}{\sqrt{2\sigma}} \int_{V_{min}}^{V_{max}} e^{\ln V} e^{-\frac{1}{2}(h(\underline{V}))^2} \mathrm{d}V} = \Phi\left(h\left(\underline{V}\right)\right) \tag{6}$$

Here Φ denotes the cumulative distribution function of the standard normal distribution and $h(\underline{V}) = (\mu + \sigma^2 - \ln \underline{V})/\sigma$. As the CDF of the standard normal distribution is strictly increasing and $h(\underline{V})$ is a decreasing function of $\underline{V}$, raising (lowering) the reporting cutoff reduces (improves) the accuracy.

Next, we determine the benefits of accuracy. These are harder to model as empirical evidence is rather scant. Social benefits pertaining to individual agents may feature either linear functions (Abowd and Schmutte 2019) or concave functions (Samuelson 1954). A sum of individual utilities even in the linear case can give a concave social benefits function (see e.g., Stern (1976) for an explanation of two sources of concavity of social welfare functions). Hence, as in Equation (1), we assume a simple increasing and concave power function with two parameters that is commonly used in economics:

$$B(A(\underline{V})) = \lambda_0 A(\underline{V})^{\lambda_1}, \tag{7}$$

where $\lambda_0 > 0$ and $0 < \lambda_1 \leq 1$. Note that a higher value of the scalar λ_0 implies higher social benefits for given accuracy and vice versa. $\lambda_1 < 1$ implies that the marginal social benefits of accuracy decline with increasing $A(\underline{V})$, whereas $\lambda_1 = 1$ implies that marginal social benefits are constant.

Using expression (6) in the social benefits function allows us to determine the marginal social benefit (the derivative of the social benefits function) of changing the reporting cutoff:

$$\frac{\mathrm{d}B}{\mathrm{d}A}\frac{\mathrm{d}A}{\mathrm{d}\underline{V}} = -\lambda_0\lambda_1\Phi(h(\underline{V}))^{\lambda_1 - 1}\phi(h(\underline{V}))(\underline{V}\sigma)^{-1} \tag{8}$$

where $\phi(.)$ denotes the density of the standard normal distribution. The marginal social benefit of increasing (decreasing) the reporting cutoff is negative (positive) for all values, as such changes reduce (increase) the accuracy. Further note that the marginal social benefits vary with cutoff non-monotonically as the second derivative $\mathrm{d}B^2/\mathrm{d}\underline{V}^2$ is either positive or negative. Namely, the second derivative of the benefits function with respect to the cutoff is $\mathrm{d}^2B/\mathrm{d}\underline{V}^2 = \lambda_0\lambda_1\Phi^{\lambda_1 - 1}\left((\lambda_1 - 1)\Phi^{-1}\phi^2(h')^2 + \phi'(h')^2 + \phi h''\right)$, where ϕ and Φ are shorthand notations for the functions that depend on function $h(\underline{V})$, which is also denoted shortly as h. The first term in the parentheses is always negative for assumed $\lambda_1 < 1$ (or 0 for $\lambda_1 = 1$), the second term is either negative or positive, whereas the third term is always positive. However, in our empirical examples, the second derivative tends to be positive, which implies that the marginal social benefit is higher at higher values of the reporting cutoff.

In order to calculate the aggregate or social cost of reporting, $C(\underline{V})$, for the loglinear cost function $c(V) = e^{\ln c_0 + c_1 \ln V}$, we calculate the following partial expectation (normalizing N to 1):

$$C(\underline{V}) = \int_{\underline{V}}^{V_{max}} c(V) \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{1}{2}\left(\frac{\ln V - \mu}{\sigma}\right)^2} \mathrm{d}V = e^{\ln c_0 + c_1\mu + \frac{c_1^2\sigma^2}{2}} \Phi\big(g(\underline{V})\big)$$

where $g(\underline{V}) = (\mu + c_1\sigma^2 - \ln \underline{V})/\sigma$. The derivative of the social cost of reporting with respect to the reporting cutoff, which can be interpreted as the marginal social cost of reporting, is also negative:

$$\frac{\mathrm{d}C(\underline{V})}{\mathrm{d}\underline{V}} = -e^{\ln c_0 + c_1\mu + \frac{c_1^2\sigma^2}{2}} \phi\big(g(\underline{V})\big)\big(\underline{V}\sigma\big)^{-1} \tag{9}$$

This expression implies that the social costs of reporting decrease (increase) when the reporting cutoff increases (decreases), although at a different rate than the marginal benefits of accuracy. Equating the two derivatives with respect to the cutoff given in Equations (8) and (9) yields:

$$\lambda_0\lambda_1\Phi(h(\underline{V}))^{\lambda_1 - 1}\phi(h(\underline{V})) = e^{\ln c_0 + c_1\mu + \frac{c_1^2\sigma^2}{2}} \phi\big(g(\underline{V})\big) \Rightarrow$$

$$\lambda_0\lambda_1\Phi(h(\underline{V}))^{\lambda_1 - 1} = e^{\ln c_0 + \mu + \frac{1}{2}\sigma^2 - (1 - c_1)\ln \underline{V}} \tag{10}$$

The optimal reporting cutoff is determined by this implicit function. Before turning to discussion of the effects of changing key parameters, note that the solutions to this equation are invariant to simultaneous re-scaling of both cost and preference parameters λ_0 and c_0 (which is also the reason we could normalize N to 1). The solution only depends on the ratio between the two, which gives some flexibility to use various measures of costs either in terms of monetary units or units of time. As long as the costs of reporting per unit of time are homogeneous across businesses (i.e., an hour of reporting bears a similar monetary cost regardless of unit characteristics), the optimal reporting cutoff will be the same.

Turning to analysis of the determinants of the optimal reporting cutoff in Equation (10), note that analytical solutions are attainable under the assumption of constant marginal social benefits of accuracy, that is, $\lambda_1 = 1$, which we also use below in our empirical application. Focusing on unique interior solutions, which exist for $c_1 < 1$ (costs of reporting are subject to economies of scale) and finite values of λ_0, the optimal reporting cutoff is:

$$\underline{V} = \exp\left(\frac{\ln c_0 + \mu + \frac{1}{2}\sigma^2 - \ln \lambda_0}{1 - c_1}\right)$$

Evidently the optimal reporting cutoff increases in both cost parameters (c_0 and c_1) and parameters that determine the mean of the lognormal distribution ($\mu + \frac{1}{2}\sigma^2$), and decreases with the parameter that reflects the weight given to accuracy in the social benefits function (λ_0).

For decreasing marginal benefits of accuracy ($\lambda_1 < 1$), we rely on numerical solutions and illustrate the determination of the optimal reporting cutoff graphically. Figure 1 shows the curves for the marginal social benefits and marginal social costs for a set of specific values from our application below in Section 4. It is evident that both the marginal social

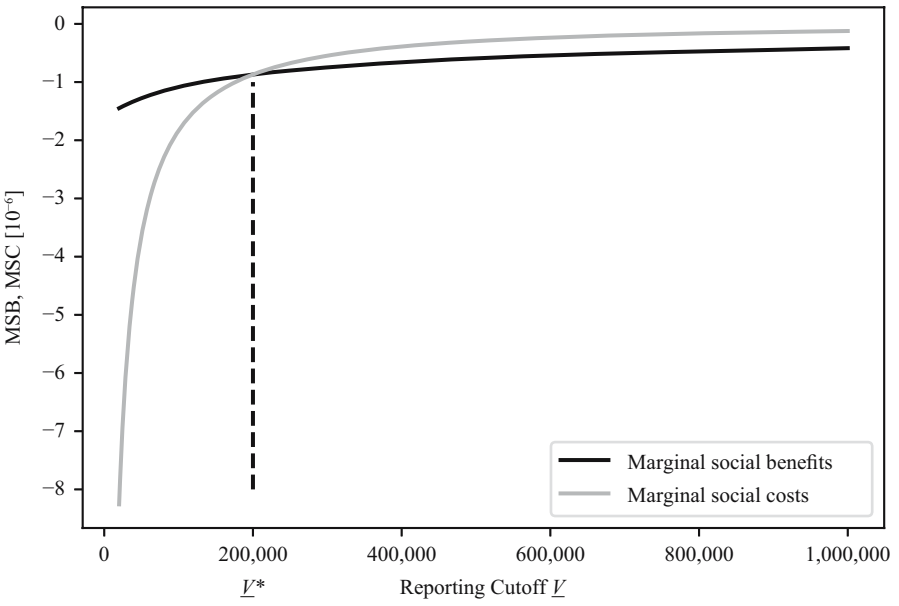


Fig. 1. Marginal social benefits and marginal social costs of reporting.
Notes: For this figure it is assumed that ln V is distributed normally with parameters $\mu = 9.233$ and $\sigma^2 = 8.111$. The cost function is loglinear with parameters $c_0 = 0.105$ and $c_1 = 0.240$. The parameters for converting accuracy into social benefits are $\lambda_0 = 7.841$ and $\lambda_1 = 0.800$. The optimal reporting cutoff $\underline{V}^*$ is at 200,000 and the corresponding accuracy is 0.9644.

benefits and costs are negative and increase with the reporting cutoff. As the marginal social costs are lower than the marginal social benefits at low cutoff values and the former also increase with cutoff at higher rates, the two curves intersect (at point $\underline{V}^*$) and determine the socially optimal cutoff. Alternatively, starting at higher values of the reporting cutoff where the marginal benefits exceed the marginal costs in absolute terms, lowering the reporting cutoff increases net social benefits (but at a decreasing rate) until the optimal cutoff is reached.

Although Figure 1 is used for illustrative purposes only, note that four (out of six) parameters are obtained from the Intrastat application in Section 4. In particular, we use the fitted parameter values for the business unit-level distribution of log (annual) values of total exports of goods from Slovenia to other EU countries in 2013 ($\mu = 9.233$ and $\sigma^2 = 8.111$). The parameters of the loglinear cost function are estimated using a survey (the 'Survey on current response burden in Intrastat' (SURS 2014); see also Perše (2016) for details) measuring the costs of reporting, completed by a set of Slovenian business units (mostly firms and sole proprietors) that were engaged in intra-EU trade in goods: $c_0 = 0.105$ and $c_1 = 0.247$. The parameters for converting accuracy into social benefits are $\lambda_0 = 7.841$ and $\lambda_1 = 0.800$, which are selected to yield an optimal reporting cutoff equal to EUR 200,000, which corresponds to the actual reporting cutoff set in Slovenia for intra-EU export flows in 2013. The corresponding accuracy is 0.9644, which is slightly below 0.97–the official lower bound for accuracy (see Regulations (EC) No 638/2004 and No 222/2009). It is important to note again that these preference parameters are not unique and we could find an alternative set of parameters that would yield the same cutoff.

For example, if we restricted λ_1 to 1, then $\lambda_0 = 6.319$ would also replicate the actual cutoff and therefore produce the same accuracy.

Next we discuss the role of changes in key parameters on the marginal social benefits and marginal social costs, and the optimal reporting cutoff values. These variations offer further insights regarding how the cutoff determination changes over time (e.g., due to shifts in all the parameters) and across different groups of respondents (e.g., businesses in different industries).

Figure 2 depicts the effects of an increase in μ, while keeping all the other parameters at the benchmark values used in Figure 1. The motivation for this increase may be found in the dynamics of values like business revenues over time, but also in differences across industries. An increase in μ shifts both marginal social benefits and marginal social costs. The higher mean implies that the distribution of V shifts to the right, which in turn lowers the marginal social benefits as less accuracy is lost at given values of the reporting cutoff. Hence the marginal social benefits curve shifts downwards. Marginal social costs are also affected by this increase as costs of reporting increase at all levels. The combined effect of these shifts leads to an increase in the reporting cutoff from 200,000 to 388,000 with a reduction in optimal accuracy by 0.0047 (from 0.9644 to 0.9597). While analysis of a shift in σ^2 is not presented in detail, an increase in variance σ^2 decreases marginal social benefits and increases marginal social costs for all cutoff values, leading to an increase in

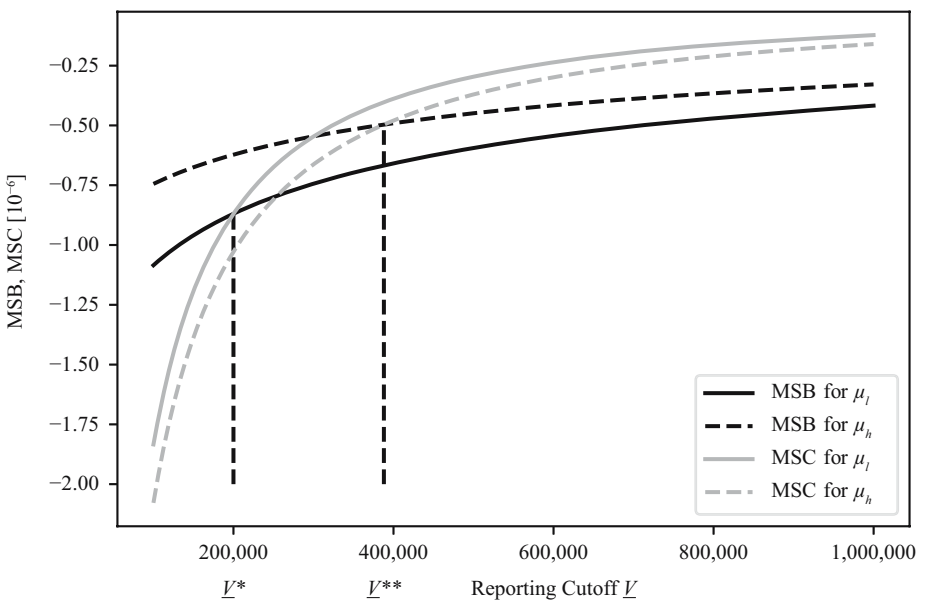


Fig. 2. The effects of an increase in μ from μ_l to μ_h on marginal social costs and benefits, and the optimal reporting cutoff.

Notes: This figure shows the impact of an increase in the mean of the lognormal distribution from $\mu_l = 9.233$ (the benchmark case) to $\mu_h = 9.733$, while keeping the variance of the distributions the same as in the benchmark case, that is, $\sigma^2 = 8.111$. The cost function is loglinear with parameters $c_0 = 0.105$ and $c_1 = 0.247$. The parameters converting accuracy into social benefits are $\lambda_0 = 7.841$ and $\lambda_1 = 0.800$. The optimal reporting cutoff $\underline{V}^*$ is 200,000 and the corresponding accuracy is 0.9644, whereas reporting cutoff $\underline{V}^{**}$ for $\mu_h = 9.733$ is significantly higher at 388,000 and the corresponding accuracy is lower at 0.9597.

the optimal reporting cutoff as well. This illustration suggests that upward (downward) shifts in means over time should be met with increases (decreases) in reporting cutoffs. Moreover, it suggests that reporting thresholds across industries should differ–industries with higher means should set higher reporting thresholds. In our empirical application we revisit these practical implications for cutoff setting.

Variation in the cost parameters is considered next. Such changes are interesting as they are likely to take place over time, but also because different groups of businesses may exhibit heterogeneous cost structures. Changes in cost parameters over time may be motivated by general technological progress, changes in the content and data collection procedures of the surveys, and changes in costs of inputs such as staff time or computer costs, whereas disparities across industries may be due to differences in economic structure that may affect reporting costs. Figure 3 shows the impact of an increase in c_0, which increases the (geometric) mean of the cost function (a shift in elasticity has a qualitatively similar effect). The marginal social cost schedule exhibits a downward shift that increases the optimal reporting cutoff from 200,000 to 282,500, and thereby leads to a reduction of accuracy by 0.0106 from 0.9644 to 0.9538. From this example we can infer that our model suggests that the reporting cutoff should be lower when technological improvements reduce the costs of reporting, higher when surveys become more detailed (increasing costs), and increase when input costs such as wages increase. Moreover, the model suggests that if cost parameters differ across industries (assuming similar

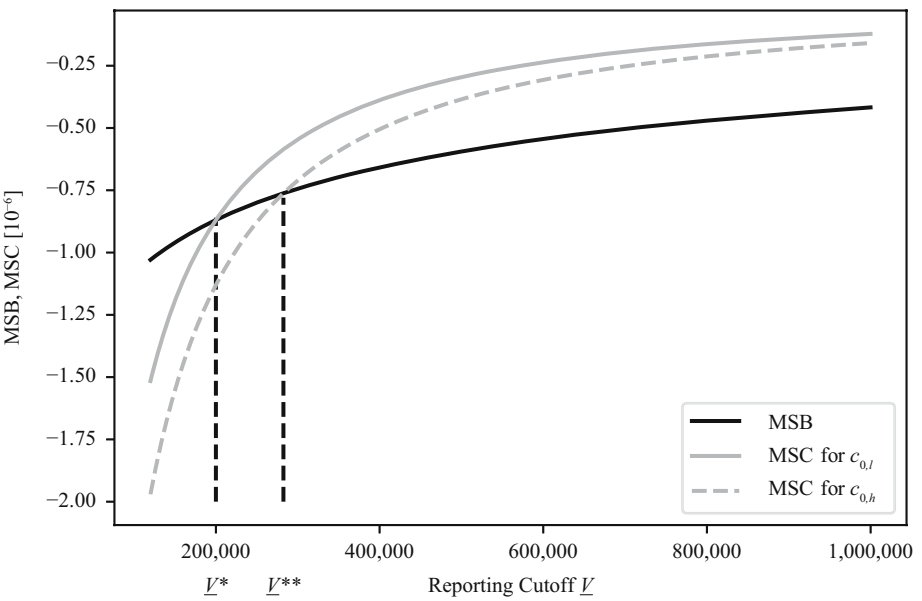


Fig. 3. The effects of an increase in c_0 from $c_{0,l}$ to $c_{0,h}$ on marginal social costs and the optimal reporting cutoff. Notes: This figure shows the impact of an increase in the cost parameter c_0 from the benchmark case $c_{0,l} = 0.105$ to $c_{0,h} = 0.1365$. All other parameters assume their benchmark values. Elasticity of costs with respect to value is $c_1 = 0.247$, ln V is distributed normally with parameters $\mu = 9.233$ and $\sigma^2 = 8.111$, and the social benefits function parameters are $\lambda_0 = 7.841$ and $\lambda_1 = 0.800$. The optimal reporting cutoff $\underline{V}^*$ is 200,000 and accuracy is 0.9644 for $c_{0,l}$, whereas reporting cutoff $\underline{V}^{**}$ for $c_{0,h}$ is 282,500 and accuracy is lower at 0.9538.

distributions $f(V)$), the reporting cutoffs should also differ. Finally, if businesses with more experience in reporting exhibit lower costs, the reporting cutoff for such businesses should be lower as well.

Our final illustration shows the impact of shifts in the parameters of the social benefits function. Figure 4 depicts an increase in λ_0; qualitatively the effects of an increase in λ_1 are similar and therefore not shown. From this figure it is evident that such a change shifts the marginal social benefits function downwards and thus lowers the reporting cutoff. While these changes are harder to motivate with practical examples, the mere fact that various surveys (e.g community innovation survey, industrial production survey) achieve different accuracies may be partly attributed to differences in the social valuations of different data sets.

4. Empirical Application: Intrastat Reporting

This section provides an application of the method of optimal cutoff determination developed in Section 2. In our illustration we discuss cutoff determination for intra-EU trade flows using data for Slovenian businesses, for which cutoff sampling is already used. As our method requires information on several parameters, an important advantage of this application is the availability of data on trade flows that allows estimation of the parameters of the distributions $f(V)$ and the cost of reporting. The key limitation of our empirical application is an inability to estimate the parameters of the function that links

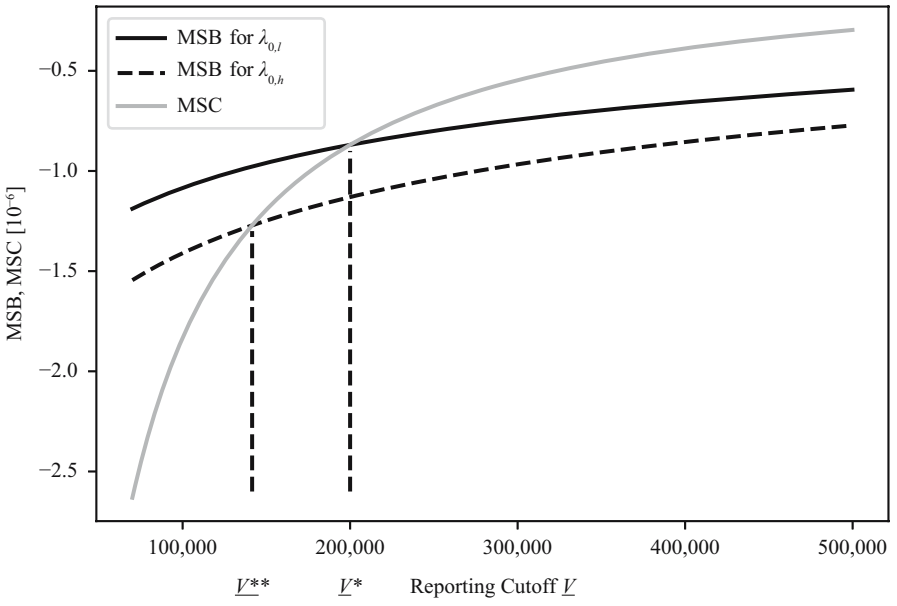


Fig. 4. The effects of an increase in λ_0 from $\lambda_{0,l}$ to $\lambda_{0,h}$ on marginal social benefits and the optimal reporting cutoff.

Notes: This figure shows the impact of an increase in the social preference parameter λ_0 from the benchmark case $\lambda_{0,l} = 7.841$ to $\lambda_{0,h} = 10.193$, while keeping $\lambda_1 = 0.800$. All other parameters assume their benchmark values. The distribution of ln V is normal with parameters $\mu = 9.233$ and $\sigma^2 = 8.111$. The cost function is loglinear with parameters $c_0 = 0.105$ and $c_1 = 0.247$. The optimal reporting cutoff $\underline{V}^*$ is 200,000 and the accuracy is 0.9644 for $\lambda_{0,l}$, whereas reporting cutoff $\underline{V}^{**}$ for $\lambda_{0,h}$ is 141,500 and accuracy is higher at 0.9729.

benefits to accuracy, which we further discuss below in Subsection 4.2. However, even without this information, using calibrated values raises important questions regarding the optimality of cutoffs used in practice.

4.1. Institutional Features of Intrastat Reporting in Slovenia

Our application uses Slovenian business unit-level data on intra-EU trade flows and a survey of a subset of these business units on response burden that was implemented for the year 2013. Therefore, we begin by setting out background information on the institutional setting for Intrastat in Slovenia. To avoid confusion, we will refer to exports and imports of goods throughout, although official terminology refers to dispatches for intra-EU exports and arrivals for intra-EU imports.

The reporting cutoffs for exports and imports in goods are set by the Statistical Office of the Republic of Slovenia (SURS). As Slovenia is a member state of the EU, SURS is obliged to comply with the aforementioned Regulations No 638/2004 and No 222/2009, which determine the lower bounds on accuracy for intra-EU reporting set by Eurostat. In 2013 the lower bounds on accuracies for intra-EU exports and imports were set to 97% of total exports and 95% of all imports of the taxable persons covered. Based on these EU-wide constraints on accuracy, SURS determined by October 31, 2012 the set of business units that were obliged to report export and import flows of goods. A business was required to report exports (imports) if it (1) was obliged to fill in and submit Value Added Tax returns and (2) had total intra-EU exports (imports) exceeding EUR 200,000 (120,000) in 2012. A business could also be added to a group of businesses reporting intra-EU trade flows within any month of the year if their 12-month cumulative trade flows (based on information on the Intrastat trade flows from the value added tax forms) exceeded the reporting cutoffs. Finally, additional reporting cutoffs were set for the collection of additional variables like type of international commercial terms, transport means and statistical value of trade, which is the net domestic value (fair market value) of a product when it crosses a border. These were set to EUR 9,000,000 for exports and EUR 4,000,000 for imports.

4.2. Data Sets

We estimate the parameters needed in determination of the optimal reporting cutoff using three main data sets obtained from three distinct sources.

A comprehensive study of response burden was conducted in May 2014 among all Slovenian businesses included in Intrastat (excluding only businesses with their seat abroad or which became part of Intrastat in 2014) (SURS 2014). For this analysis, we used data from businesses that reported data to Intrastat themselves (from $n = 3{,}579$ units, 2,141 responded, yielding a response rate of 59.9%; see Perše (2016) for more details). These data were used to estimate the parameters of the cost functions. Survey respondents were also asked to state their tax office registration number, which allowed SURS to match the data from the response burden survey with other key business-unit-level information. For our illustration we use information on the value of exports and imports in 2013, broad sectors of economic activity (manufacturing, trade and other industries), the numbers of records or distinct reporting items (i.e., distinct records are due to differences in country of

consignment/destination, delivery terms, nature of transaction, mode of transport, and country of origin), trading partners, countries and products (the latter based on the Standard International Trade Classification, SITC); and past obligation to report intra-EU trade flows up to five years back.

Businesses that report through a declarant ($n = 2{,}675$) and declarants themeselves ($n = 927$) were surveyed separately and are not included. Compared to the Intrastat population, our sample has relatively fewer micro units and relatively more larger units with more trade (5% of responding units were large compared to 4.1% among units that report themselves and 1.9% among units that report through a declarant). Additionally, we have to take into account that units below the officially determined cutoffs for reporting intra-EU trade were not surveyed. The moments of such a truncated distribution are severely biased as estimators of the full distribution, which is the motive for the use of an alternative dataset on Intrastat trade flows that is collected jointly by SURS and the Slovenian Financial Authority (SURS and FURS 2014). While the same cutoffs should apply to Intrastat trade, many business units nevertheless report trade volumes below the cutoff, partly because obligation to report is determined on the basis of past trade flows. From this source we use total values of exports and imports. Using business-level identifiers we also add broad sectors of economic activity from annual business accounts (Agency of the Republic of Slovenia for Public Legal Records and Related Services, henceforth AJPES).

Finally, as the estimated moments of the distributions from Intrastat are nevertheless likely to be biased, we also consider a data set on intra-EU trade from the Annual Business Accounts of businesses (AJPES 2014). From this source we obtain total values of exports within the EU. Although this data set does not suffer from truncation, it excludes information on exports of sole proprietors and other business units, and contains information on sales of both goods and services (whereas Intrastat covers only goods).

4.3. Descriptive Statistics

Table 1 shows descriptive statistics for the responding sample of business units with information on response burden, separately for export and import flows, that is used in estimation of the cost functions. Of 2,141 business units, 872 reported total time needed to fill the Intrastat forms on export flows, and 1,855 reported on import flows (see Appendix 3 in Perše (2016) for more information on the representativeness of the sample).

Table 1 contains descriptive statistics for original variables and log-transformed variables for the reference year 2013. From the top panel of this table it is evident that the average surveyed exporting (importing) business needed 6.6 (9.3) hours per month or roughly 80 (111) hours per year to complete the Intrastat questionnaires. The average value of intra-EU exports (imports) within this truncated sample was EUR 7.9 (4.1) million. Note that these values are significantly higher than the corresponding averages reported in Table 3 for the sample of all 2013 Intrastat reporters–these were EUR 0.87 (0.403) million. Due to this discrepancy, we expect that the estimated cost function parameters are not consistent and possibly suffer from selection bias. Table 1 also shows the descriptive statistics for the numbers of records, products, partners and countries of reported flows. The average surveyed exporting business unit within this sample sells 21

Table 1. Summary statistics for key variables for 2013 from response burden sample

	Exports			Imports		
	Observations	Mean	S.d.	Observations	Mean	S.d.
		Levels				
Reporting time (hrs)	872	6.6	10.6	1,855	9.3	15.0
Value (m EUR)	911	7.9	36.4	1,925	4.1	23.4
Products	911	20.9	38.9	1,936	55.9	93.5
Partners	930	36.6	90.6	1,925	33.2	55.8
Countries	911	6.9	6.1	1,919	5.8	4.1
Records	911	342.6	1,191.7	1,925	590.7	2,272.8
		Logs				
Reporting time	872	1.17	1.18	1,855	1.49	1.20
Value	906	13.94	1.85	1,919	13.29	1.70
Products	906	2.13	1.36	1,919	3.18	1.41
Partners	930	2.71	1.30	1,936	2.87	1.11
Countries	906	1.53	0.96	1,919	1.49	0.79
Records	911	4.43	1.59	1,925	4.93	1.72

Source: Survey on current response burden in Intrastat, May 2014 (SURS 2014).

products to 37 partners in seven countries and has 342 corresponding records. In contrast, its importing peer buys on average 56 products from 33 partners in six countries and has 590 records of these activities. We can see that import flows are significantly more dispersed than export flows, which likely contributes to the higher reporting time–even for lower transaction values.

The bottom panel of Table 1 also shows the descriptive statistics for log-transformed variables, which are used in cost function estimations. In order to give some indication of the direction and strength of correlations between these variables, Table 8 in Appendix, Subsection 6.2, also contains correlation coefficients, separately for exports and imports. All variables are positively correlated; most importantly, reporting time is particularly strongly correlated with numbers of products and records, which suggests that businesses more engaged in reporting also have more disaggregated trade flows.

As already mentioned above, Perše (2016) merged the data from the SURS survey (SURS 2014) on response burden with administrative data providing the broad sector of the respondent's main economic activity (from AJPES), distinguishing between manufacturing, trade, and other industries. For these sectors Table 2 presents further summary statistics for the two main variables of interest: value of trade flows and reporting time. From these statistics it is evident that business units in manufacturing businesses have the highest mean values for both values of trade flows and reporting times. However, differences in mean trade values do not seem to translate into differences in reporting times, suggesting important differences in the structure of trade flows. For example, the mean number of records (not shown in the tables) is the highest for 'manufacturing' among exporters, but not among importers.

The next set of descriptive statistics features estimates of the moments of the distribution of the value of transactions from the full sample of Intrastat reporters in 2013. As discussed above, we do not use the estimates of the mean and variance from Table 1 for the value of trade due to truncation of the distributions below the cutoffs set at EUR 200,000 for exports

Table 2. Trade flows and reporting times (in logs) for 2013 by sector.

	Exports				Imports			
	Value		Reporting time		Value		Reporting time	
Sector	Mean	S.d.	Mean	S.d.	Mean	S.d.	Mean	S.d.
All	13.945	1.847	1.173	1.177	13.296	1.699	1.486	1.203
Manufacturing	14.405	1.819	1.306	1.202	13.667	1.803	1.572	1.208
Trade	13.256	1.645	1.077	1.151	13.262	1.585	1.523	1.191
Other	13.527	1.827	0.838	1.040	12.698	1.640	1.217	1.195

Source: Survey on current response burden in Intrastat, May 2014 (SURS 2014).
Note: All variables are log transformed.

and EUR 120,000 for imports. The full sample of Intrastat reporters also suffers from truncation, as many businesses below the cutoffs do not report trade flows. However, the samples of exporting and importing businesses above the cutoffs are 2,538 and 5,181 business units, whereas the full samples used for the estimations of the moments given in Table 3 are 16,575 and 33,978 business units, respectively. The average value of exports (imports) for these larger samples are EUR 0.87 (0.40) million, which is significantly lower than the averages reported in Table 1 for the sample of businesses filling the response burden survey. Nevertheless, given that reporting under the cutoffs was still incomplete, the parameters for the lognormal distribution are likely still biased. The estimates of means (variances) are likely upward (downward) biased. In cutoff determination below we use the means and squared standard deviations for the log-transformed variables. In our basic cutoff determination exercise we use the estimates of means and variances for log transformed values given in Table 3 (these values were also used in the illustrations of the method in Subsection 3.2). The distributions of log transformed values of exports and imports for all observations are depicted in Figure 5. Evidently, these are fairly closely approximated with normal distributions. The three economic sectors have similar shapes of distributions, but different values of mean and dispersion.

The final set of statistics refers to the sample of businesses for which we have information on all intra-EU exports (including exports of services) that is collected in annual business accounts. This sample contains a complete set of businesses, but excludes

Table 3. Summary statistics for the values of imports and exports (in logs) for the full sample of Intrastat reporters, 2013.

	Exports			Imports		
	Observations	Mean	S.d.	Observations	Mean	S.d.
All	16,575	9.233	2.848	33,978	8.913	2.701
Manufacturing	4,268	10.530	3.110	6,178	9.721	2.856
Trade	5,213	9.498	2.680	10,181	10.049	2.598
Other	7,094	8.258	2.417	17,619	7.979	2.356

Source: SURS and FURS (2014) and AJPES (2014).
Note: All variables are log transformed.

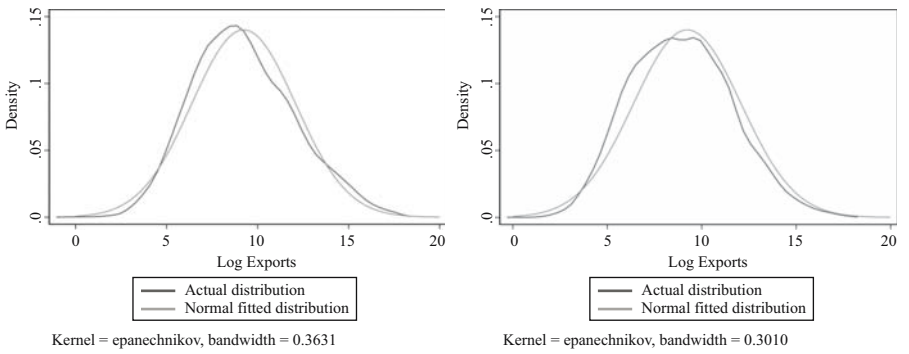


Fig. 5. Actual and fitted distributions of the values of exports and imports (in logs) for the full sample of Intrastat reporters, 2013.
Source: SURS.
Notes: All variables are log transformed. The actual distributions are smoothed kernel density plots.

Table 4. Summary statistics for the values of exports of goods and services (in logs) for the full AJPES sample, 2013.

	Observations	Mean	S.d.	Accuracy
All	12,797	10.487	2.743	0.981
Manufacturing	2,912	11.597	2.995	0.993
Trade	4,113	10.183	2.562	0.959
Other	5,752	10.143	2.584	0.964

Source: AJPES (2014).
Note: All variables are log transformed.

sole proprietors. In the construction of the sample used for calculation of the moments of the distribution, we follow the EU regulations and exclude businesses that are not obliged to pay value added tax. This reduces the final sample of businesses from 15,382 to 12,797 with total value of exports EUR 18.667 billion. For these businesses we again calculate means and standard deviations for all businesses and three economic sectors (Table 4). Comparison of the moments reveals that the exclusion of sole proprietors and addition of service flows yields higher means and mostly lower standard deviations. In addition to these statistics we are able to calculate the measure of accuracy using the full samples and samples restricted by the EUR 200,000 reporting cutoff. Note that we apply both VAT status and inclusion in reporting based on 2013 data, which makes the accuracy calculated here comparable to that reported in the determination of the optimal cutoff below. From these measures of accuracy we can observe that actual accuracy varies across sectors between 95.9% in trade and 99.3% in manufacturing, while overall accuracy is 98.1%. Accuracy in trade and other sectors is thus below the required 97%. Not surprisingly, application of the same cutoff at industry level reveals even greater variation in accuracy, some industries achieving accuracy close to 80%.

4.4. Cost Function Estimation and Cutoff Determination

In this section we estimate the cost functions using the sample of observations from the SURS survey (SURS 2014). Based on these estimates, the estimated moments of the

distributions for the values of trade flows and the assumed benefits functions, we determine the optimal reporting cutoffs.

The parameters of the cost function (c_0 and c_1) are estimated from the following loglinear equation:

$$\ln C_i = \ln c_0 + c_1 \ln V_i + \varepsilon_i \tag{11}$$

which can be done using the ordinary least squares method. We estimate this equation separately for different types of trade flows (exports and imports) and different sectors of economic activity (all sectors, manufacturing and trade) in order to allow for heterogeneity of parameters.

Table 5 shows the estimated coefficients based on constant marginal benefits of accuracy, $\lambda_1 = 1$, in Equation (7). The elasticity of reporting time (parameter c_1) is between 0 and 1 for both types of flows and all economic sectors, while the estimated constant is always negative and the corresponding parameter c_0 is small, but positive. The most interesting observation is that the parameters are significantly different between the sectors (and the same direction of flow), with manufacturing having a lower constant than trade (the difference for exports is $-3.266-(-0.765) = -2.501$ with $p<0.001$, whereas for imports it is $-3.044-(-1.716) = -1.328$ with $p = 0.004$) and higher elasticities (the difference for exports is $0.320-0.139 = 0.181$ with $p<0.001$ and for imports it is $0.339-0.245 = 0.094$ with $p = 0.006$). The estimates for the two trade flows within a sector are similar, and significantly different only in elasticity for the trade sector (the difference is $0.139-0.245 = -0.106$ with $p = 0.003$).

Table 6 shows optimal reporting cutoffs calculated with the estimated values of parameters for the cost functions and the moments of the distributions. Given our ignorance regarding the values of parameters of social preference for accuracy, we first calibrated parameter λ_0, while assuming λ_1 to be equal to 1. Calibration was done for estimated paramaters of costs and trade value distributions for all sectors jointly to replicate the official cutoffs, that is, EUR 200,000 for exports and EUR 120,000 for imports. Calibrated λ_0's are equal to 6.319 (6.849) for exports (imports) with corresponding accuracies at 0.9644 (0.9526).

Table 5. Estimates of cost function parameters.

	Exports			Imports		
	All sectors	Manufacturing	Trade	All sectors	Manufacturing	Trade
c_1	0.247**	0.320**	0.139**	0.268**	0.339**	0.245**
	(0.021)	(0.027)	(0.042)	(0.015)	(0.024)	(0.023)
log c_0	-2.251**	-3.266**	-0.765	-2.073**	-3.044**	-1.716**
	(0.288)	(0.393)	(0.562)	(0.206)	(0.335)	(0.310)
Observations	855	480	265	1,836	599	923
Adj. R^2	0.144	0.222	0.036	0.142	0.243	0.107

Source: Own calculations based on Survey on current response burden in Intrastat, May 2014 (SURS 2014).
Notes: This table shows the estimates of parameters from a regression of log reporting time on log of values of exports (imports), using Equation (11).
***,**,* indicate statistical significance level at 0.1,1 and 5%.

Table 6. Optimal reporting cutoffs by sectors and direction of trade flows.

	Exports			Imports		
Parameters	All sectors	Manufacturing	Trade	All sectors	Manufacturing	Trade
λ_0	6.319	6.319	6.319	6.849	6.849	6.849
λ_1	1.000	1.000	1.000	1.000	1.000	1.000
μ	9.233	10.530	9.498	8.913	9.721	10.049
σ^2	8.111	9.673	7.182	7.295	8.157	6.750
c_1	0.247	0.320	0.139	0.268	0.339	0.245
c_0	0.105	0.038	0.465	0.125	0.047	0.179
V^*	200,000	3,533,930	193,170	120,000	630,650	423,200
$\overline{A}(V^*)$	0.9644	0.9503	0.9538	0.9526	0.9434	0.9305
Relative RMSE	0.0356	0.0497	0.0462	0.0474	0.0566	0.0695

Source: Own calculations based on AJPES (2014), SURS (2014) and SURS and FURS (2014).

The optimal reporting cutoffs for the manufacturing and trade sectors calculated with the calibrated preference parameters are quite different from the official cutoffs, and consequently also produce different accuracies. For the manufacturing sector in particular we observe significantly higher cutoffs, which we can attribute primarily to the larger mean and variance of the distribution. For example, the optimal cutoff for reporting intra-EU export flows in the manufacturing sector is around EUR 3.5 million, which is primarily due to the larger mean and variance of the distribution of export values (for the cost parameters obtained for all businesses, the optimal cutoff would be EUR 3.15 million). Despite the higher cutoffs, we have a rather modest decline in accuracy by roughly one percentage point. More generally, we can observe that optimal cutoffs may increase or decrease. For exporting businesses in the trade sector these should increase, whereas for importing businesses in both the manufacturing and trade sectors they should decrease.

As a robustness test we also consider cutoff determination based on total intra-EU exports of goods and services (see Table 7). We follow the same approach as above and initially calibrate the parameters of social benefits of accuracy to data for all sectors using the actual cutoff (EUR 200,000). Based on this cutoff we can see that for the lognormal distribution accuracy is very close to the actual value (0.981 versus 0.983), which suggests that use of the lognormal

Table 7. Optimal reporting cutoffs by sectors using intra-EU exports of goods and services.

Parameters	All sectors	Manufacturing	Trade
λ_0	16.510	16.510	16.510
λ_1	1.000	1.000	1.000
μ	10.487	11.597	10.183
σ^2	7.524	8.970	6.564
c_1	0.247	0.320	0.139
c_0	0.105	0.038	0.465
V^*	200,000	2,464,000	243,560
$\overline{A}(V^*)$	0.9828	0.9746	0.9800
Relative RMSE	0.0172	0.0254	0.0200

Source: Own calculations based on AJPES (2014), SURS (2014) and SURS and FURS (2014).

distribution as an approximation is a reasonable choice. Based on the calibrated value of social preference for accuracy, which is now somewhat higher (16.51 versus 6.319), we again determine the cutoffs for manufacturing and trade using the same estimated parameters for cost functions and distributional moments based on the full sample of exporting businesses. We can see that the optimal reporting cutoff for both manufacturing and trade is higher than the official cutoff, although for manufacturing the difference is again extremely large. Our approach to cutoff determination suggests that taking into account the costs and benefits, reporting in manufacturing in particular should have a higher reporting cutoff and lower accuracy.

5. Discussion

5.1. Implications and Operational Considerations

In this article we have proposed a simple theory for determining the threshold in cutoff sampling that uses the trade-off of the costs and benefits of accuracy (defined as the proportional coverage of the total value of the variable of interest). The cutoff is determined by an optimisation that maximizes the net social benefits. For specific distributional assumptions on the variable of interest, the respondents' cost function and the social benefits function, we are able to derive analytical expressions for the cutoffs or (if that is not possible) provide numerical solutions.

We show that the optimal cutoffs increase with the mean and variance of the distributions and the preference for accuracy, and decrease with the reporting costs of survey respondents. This research exposes the trade-offs that are implicit in the cutoff determination in surveys of this type, thus contributing to an increased transparency that is also advocated by the European Statistics Code of Practice (Eurostat 2018).

We show how our approach could be used in practice by utilising a survey on Intrastat respondents' costs in Slovenia that allows us to estimate the cost function parameters. By combining the estimated cost parameters with estimates of the mean and variance of the distribution of the variable of interest and the calibrated social benefits function parameters, we are able to calculate the optimal cutoffs. By calibrating the social benefits function parameter to match the actual cutoffs used in Intrastat in Slovenia in 2013, we find that the optimal cutoffs in specific industrial sectors differ significantly. In the manufacturing sector the costs of reporting are higher and the mean and variance of the values of exports are higher, which together imply much higher optimal cutoffs than those set in practice. In most EU countries, the cutoffs change infrequently over time (see the national exemption thresholds in national currency between 2017–2020 in Eurostat (2021b, Table A.2.2)). For example, in Slovenia the cutoff set by SURS for export flows was EUR 200,000 between 2008 and 2017. When the economy was growing, the accuracy of total exports based on this cutoff was increasing, whereas during the great depression in 2009 accuracy decreased (results not shown).

One of the most striking implications of this approach to setting cutoffs is that during sharp changes in economic activity when the mean and variance change significantly, the cutoffs should be adjusted as well. In a similar way, cutoffs should be allowed to differ across sectors (and possibly industries), to maintain the optimum social benefits of the survey. In particular, manufacturing bore too large a burden in 2013 in our application because of the uniform cutoff. To achieve the optimum cost-benefit trade-off in the future,

the response burden on manufacturing should be relieved by increasing the cutoff and sacrificing some accuracy.

These findings present some operational challenges for a NSI, since the true cutoff for a given year depends on the mean and variance of the survey variable and the estimated costs in that year, and neither is available at the time that the reporting cutoff is set. However, information from the previous year can be used to provide mean and variance estimates to allow forecasting of the cutoffs. When there is a particularly dramatic change in economic conditions, some adjustment to annual cutoffs may be needed.

Reporting costs are not expected to change rapidly, but the collection of data on burden should continue, preferably for all units (to provide the information to make the management of the burden possible).

There is an operational argument for a constant cutoff across all industry sectors, which is based on simplicity. However, it is not *fair* in the sense measured by our cost-benefit trade-off, and using an approach such as the one we propose here seems to present a more equitable sharing of the burden of responding across businesses. How far the idea of varying cutoffs can be extended is an interesting question. Potentially, businesses reporting through declarants will have different costs to those who report directly, and this could be handled by putting these businesses in separate strata with different cutoffs. Similarly, businesses new to the survey could be separated, as they typically have higher costs than businesses which have established procedures. But handling a larger number of strata leading to a large number of different cutoffs according to business characteristics is challenging and may be too complex to implement.

5.2. *Extensions*

The approach used in this article is based on a cost-benefit trade-off, because there are sources available with which the parameters can be estimated. Ideally, however, this approach would be extended to a full social benefits function, which requires information reflecting the social benefits of accuracy. Future research should focus on measuring these benefits, which will require more investment in understanding the uses and users of these data. The concept of measuring the effects of accuracy seems a bit narrow in this context; it applies principally to established uses, while data archives prove that the same data may be used for very different purposes. Progress in this direction is likely to be challenging as illustrated with an assessment of the consequences of population census inaccuracy for apportionment of the U.S. House of Representatives and for allocation of federal funds (Spencer and Seeskin 2015). For an overview of the public good of statistics see Office for Statistics Regulation (2020).

In a similar way, the cost functions could be extended to include other cost components, for example the cost to the NSI of running the survey. This would present a second cost variable, which would need to be included through its effect on social welfare (for example noting that additional costs for the survey have an opportunity cost for other statistical outputs, or even for other government functions).

Aside from the social benefits function, future research should focus on more general and possibly more realistic distributions for key variables of interest, such as the

generalized Gamma distribution, which includes the lognormal distribution as a special case, but also allows more flexibility in its shape.

To improve the estimates of the cost function parameters, more attention could be paid to obtaining information on reporting costs of smaller units, below the cutoff values. Although the smallest businesses are not required to report, some of them do, so it is in principle possible to collect this information. Similarly, obtaining larger responding samples would allow for more accurate estimation. Extending the estimation to the parts of the business population which report through a declarant may also modify the cost parameters and therefore the cutoffs; it is an open question whether these differences are best reflected in separate cutoffs or pooled in calculating a common cutoff.

Our exposition and application are focussed on the benefits of the accuracy of the aggregate values. The impact on more detailed levels (of either variables or classifications) is not considered. Some additional complications arise in dealing with multiple components rather than an aggregate value. However, we reflect the process in Intrastat (and other similar surveys), where the reporting cutoff is set on a single, aggregate variable, with no explicit control of lower level breakdowns. In principle, of course, the currently used Intrastat cutoffs may be set artificially low to protect against poor accuracy of estimates for breakdowns.

We examined a situation where the cutoff variable is defined on past administrative information about the variable of interest, assuming that it is a strong predictor. We may also consider the situation where the cutoff variable is only a proxy for the variable measured in the survey, which will weaken the relationship. Baillargeon and Rivest (2009) discuss the design of stratified samples when the stratification variable differs from the response variable, and this approach could be applied in our context; we leave this for future research.

A natural extension is to make an estimate for the excluded part of the population, E, based on auxiliary information (which may include the variable used to define the cutoff). This should reduce the impact of the cutoff approach on the quality of estimates, compared with the strategy of neglecting the cutoff used in this article. This will link better to the use of estimates other than of totals (such as means and ratios), which implicitly include such compensation.

5.3. *Conclusion*

We have demonstrated that it is possible to set cutoffs in cutoff sampling in a way which optimises a simple cost-benefit trade-off. This objective framework offers a new direction for managing burden in official statistics with this type of design, and gives a framework for evaluating the fairness of the burden in existing surveys. The availability of information on costs of reporting is an essential component of this approach, and these data should be routinely collected.

6. Appendix

6.1. *Cutoff-Determination for Pareto Distributed Variables*

In Subsection 3.2 of the main text we assumed that the key variable of interest is distributed according to a lognormal distribution. While this assumption may be relevant

for many variables like businesses' revenues, it may not be the best choice for variables like employment, which do not feature a bell-shaped distribution. Instead, a more appropriate distribution may be the Pareto (Axtell 2001; Gabaix 2009). In this Appendix we provide analytical results for the optimal reporting cutoff assuming the variable of interest is Pareto distributed.

Let us assume a probability density function $f(V) = \alpha \frac{V_{min}^{\alpha}}{V^{\alpha+1}}$. We assume $\alpha > 1$, which ensures the existence of a finite mean for V. (Alternatively, we could impose an upper bound on the domain of the reporting variable, which would allow calculation of means also for $\alpha = 1$.) For this functional form, the measure of accuracy is a power function of the reporting cutoff, algebraically, $A(\underline{V}) = (\underline{V}/V_{min})^{1-\alpha}$. Assuming the benefits function in Equation (7), the marginal benefit of changing the reporting cutoff is $\mathrm{d}B/\mathrm{d}\underline{V} = \lambda_0\lambda_1(1-\alpha)\underline{V}^{(1-\alpha)\lambda_1-1}V_{min}^{(\alpha-1)\lambda_1}$, which is negative for the assumed parameters ($\alpha > 1$, and $\lambda_0, \lambda_1 > 0$). Hence a decrease in the reporting cutoff increases the benefits pertaining to accuracy and vice versa.

Assuming a log-linear reporting cost function yields a closed-form solution to the net social benefit maximization problem. Assuming such a cost function, again with two parameters, $c(V) = c_0 V^{c_1}$, where $c_0 > 0$, $c_1 < \alpha$ and $1 + c_1 - \alpha > 0$, the functional form for the aggregate reporting cost is $C(\underline{V}) = c_0 V_{min}^{\alpha} \int_{\underline{V}}^{\infty} V^{c_1-\alpha}\mathrm{d}V$, which can be further expressed as $C(\underline{V}) = -\frac{c_0 V_{min}^{\alpha}}{1+c_1-\alpha}\underline{V}^{1+c_1-\alpha}$. The marginal cost of changing the reporting cutoff is $\mathrm{d}C(\underline{V})/\mathrm{d}\underline{V} = -c_0 V_{min}^{\alpha}\underline{V}^{c_1-\alpha}$. The analytical solution to the first-order condition $\frac{\partial NSB}{\partial \underline{V}} = 0$, yields

$$\underline{V} = \left(\frac{\lambda_0\lambda_1(\alpha-1)}{c_0 V_{min}^{(\alpha-1)\lambda_1-\alpha}}\right)^{\frac{1}{1+c_1-\alpha-\lambda_1(1-\alpha)}}. \tag{12}$$

This expression only yields an economically sensible solution when the following condition on the model parameters holds: $1 + c_1 - \alpha - \lambda_1(1-\alpha) < 0$. Assuming this condition does hold, an increase in the preference parameters λ_0 and λ_1 – which increase valuation of accuracy – leads to a lower reporting cutoff. Moreover, an increase in the parameters capturing the costs of reporting predicts a higher reporting cutoff. For $\alpha > 1$ and $0 < \lambda_1 < 1$, the above inequality holds when the variable costs of reporting increase sufficiently slowly, that is, c_1 must be sufficiently close to 0.

6.2. Additional Descriptive Statistics

Table 8. Correlation coefficients for the key variables from response burden survey.

	Reporting time	Value	Countries	Products	Partners	Records
			Exports			
Reporting time	1.000					
Value	0.382	1.000				
Countries	0.328	0.549	1.000			
Products	0.431	0.402	0.488	1.000		
Partners	0.386	0.525	0.741	0.513	1.000	
Records	0.470	0.676	0.695	0.764	0.678	1.000
			Imports			
Reporting time	1.000					
Value	0.377	1.000				
Countries	0.367	0.525	1.000			
Products	0.517	0.530	0.584	1.000		
Partners	0.443	0.543	0.733	0.597	1.000	
Records	0.506	0.652	0.561	0.880	0.543	1.000

Source: Survey on current response burden in Intrastat, May 2014 (SURS 2014).
Note: Variables are log transformed.

Table 9. Estimates of cost function with an extended set of regressors.

	Exports	Imports
Value (log)	0.098**	0.180**
	0.027	0.030
Records (log)	0.132**	0.132**
	0.050	0.033
Products (log)	0.169**	0.206**
	0.043	0.038
Partners (log)	0.136**	0.262**
	0.043	0.034
Markets (log)	-0.105	-0.074
	0.059	0.046
Experience (years)	-0.015	-0.030
	0.013	0.008
$D_{both\ flows}$	0.133	-0.077
	0.095	0.055
Const.	-1.318	-0.842
	0.303	0.211
Adj. R^2	0.252	0.311
Observations	852	1,835

Source: Own estimates based on data from Survey on current response burden in Intrastat, May 2014 (SURS 2014).
Notes: ***,**,* indicate statistical significance level at 0.1,1 and 5%.

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