On the optimal design of operational risk data consortia*

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Abstract

To manage operational risk banks increasingly use data coming from data consortia formed by peer institutions. Although existing data consortia seem to work appropriately, it is worth examining why banks report properly (that is, thoroughly and truthfully), since in several countries where new data consortia are planned to be set up, there are fears that banks may choose to report untruthfully or hide information (what we call misreporting). We show that if misreporting cannot be detected, then even in an infinitely repeated setup the game has multiple equilibria, so proper reporting is not the unique outcome. Then we analyze two types of sanctions. When the punishment is non-monetary (e.g. exclusion from the consortium for a given number of periods), then for some parameter values even the harshest punishment cannot bring about proper reporting as the unique outcome. Nonetheless, a numerical example suggests that by designing adequately the data consortium, proper reporting can be advanced, without overly compromising anonymity. When a monetary fine is imposed on misreporting banks, then a sufficiently sever punishment results in proper reporting, even if anonymity is maintained in the limit.

Keywords: operational risk, risk management, data consortia, repeated games, (non-)monetary punishment

JEL Classification:C73, G21, G32

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1 Introduction

Although operational risk has affected financial institutions throughout their history, the last two decades saw a dramatic increase in the attention devoted to it. A number of highly publicized and costly fraudulent events related to operational risk (e.g. rogue trading at Barings and at Daiwa Bank in 1995 and at Société Générale in 2008) led to the recognition of operational risk as a major standalone risk. As a consequence, the Basel Capital Accord (the so-called Basel II framework) separated it explicitly from credit and market risks and set specific regulatory standards to manage it. The Basel Committee on Banking Supervision defined operational risk as "the risk of loss resulting from inadequate or failed internal processes, people and systems or from external events". The importance of operational risk management is also highlighted by the fact that banks allocate a considerable part of their capital to it.[1]

If a risk event has not materialized at the individiual institutional level, it does not mean that there is no risk exposure. To overcome this problem, banks have come to rely increasingly on external data and they are using operational loss experience from peer institutions to improve their risk management - as an input to both statistical-econometric models and to qualitative techniques such as benchmarking or risk assessment. External data come from public and consortium-type databases. In the latter case, financial institutions report, pool and share data on operational risk events with each other on a voluntary basis (see, for instance, Voit (2007) or Wood (2007)). Examples include ABA (US), DAKOR (Germany), DIPO (Italy), DSGV Datapool (Germany), GOLD (UK), HunOR (Hungary) and ORX (international). European operational risk data consortia have regular meetings in order to share experiences.[2]

Reporting standards vary across data consortia, but the following information is generally required: classification data about the origination of the event (e.g. business line, event category, country, etc.), reference dates (date of occurence, discovery and recognition) and the amount of loss. Generally, consortia also require a description of the case. The more detailed the information about an operational risk event, the more helpful it is for other banks to learn from it. However, secrecy is an integral part of bank management, as banks do not like to disclose internal information. This is especially true for data on failures. For this reason anonymity is of utmost importance in any data consortium. Without a high level of anonymity banks would be reluctant to participate. That is why, along with the data already mentioned, banks are required to also send scaling factors and indicators for anonymization purposes. Using these factors the consortium might transform the data so that the source bank cannot be identified.

[1] According to a survey (Basel Committee on Banking Supervision (2009)), 7.5 % of the consolidated Tier 1 capital of the surveyed banks is allocated to operational risk. Publicly available information indicates that this share is even higher for large international banks. According to their 2012 Annual Reports, J.P. Morgan Chase and Deutsche Bank allocated USD 15.9 billion and EUR 5 billion to operational risk, corresponding to 18 and 17 % of their total economic capital, respectively.

[2] See, for insatnce, DIPO events at: http://www.dipo-operationalrisk.it/EN.

There is a natural tension between the desire to have detailed reports about other banks' operational events and low willingness to share information about own experiences. In the presence of a high level of anonymity (i.e. anonymity not only in a bank-to-bank relationship, but also in the case of bank-to-data manager relationship), banks may not do their best when reporting, for example not reporting truthfully or hiding operational risk events. Yet, if careless and unreliable reporting (henceforth, misreporting) becomes generalized, then the information obtained from the consortium loses its value and the consortium may break down. These considerations should be taken into account setting up such a data-sharing arrangement. John Rumsey (2011) reports difficulties about setting up operational risk loss databases in Latin America because banks fear the loss of confidentiality.[3] He also notes that even if a database is set up (e.g. in Argentina participation in a database is mandatory), banks may react to such fears by concealing information and not reporting thoroughly and carefully. Hence, it seems important to understand why a bank would choose to report untruthfully. In this paper, we examine the incentives to start reporting untruthfully in a data consortium.

First, we study the consequences of having a very high level of anonymity that does not allow the detection of misreporting. *Ex ante* identical banks are hit by an operational shock in each period. The operational shock is binary, with the large shock representing the low frequency - high severity events. Small shocks exemplify the high frequency - low severity events. They form a data consortium to improve their risk management. Banks may report truthfully their operational risk event or choose to misreport to the consortium that computes a set of information based on the reports. This set of information is used to manage their operational risk. The benefits of being a member of the data consortium come through enhanced operational risk management only if the external data are of good quality. If a set of information provided by the data manager is believed to be based on poor data, then banks prefer to disregard it. More precisely, a set of information is assumed to be useful only if *all* the other banks have reported truthfully. Furthermore, it is assumed that in the latter case the set of information is valuable for an individual bank even though that bank misreports. This assumption captures the idea that an individual bank would prefer above all to have the truthful data of all other banks without having to reveal its own operational losses. The cost of participating in a consortium is related to the additional efforts implied by reporting and the potential negative effects if information about the loss becomes public due to leakage. Banks do not monitor the actions of other banks, a feature that exacerbates cooperation. In fact, in the one-shot simultaneous game misreporting is the dominant strategy if misreporting cannot be detected. If banks generally misreport, then the data consortium is dysfunctional and loses its *raison d'être*. However, data consortia are established over an indefinite horizon, so it is natural to think about banks participating in a repeated game. Even if misre-

[3] In personal communication, Gergely Szabolcs told us about the same kind of fears reported by Russian bank officers at a conference that dealt with the possibilities of establishing operational risk loss databases in Russia.

porting is unobservable, with infinitely repeated interactions truthful reporting in each period becomes a possible outcome, but not the unique one. We argue that in countries where data consortia work appropriately, prevailing norms and cultural factors (the study of which is beyond the scope of this paper) may enforce the efficient equilibrium. However, it is not guaranteed that in other countries similar forces select the same equilibrium. Potentially, in the absence of any central authority data consortia may not work adequately. Therefore, we introduce the possibility that a supervisor detects misreporting with some probability. This violates anonymity, but it helps to implement truthful reporting as a unique outcome by using punishment. Two possible forms of punishment are examined. In the case of non-monetary punishment, detected misreporting implies exclusion from the data consortium for a finite time horizon. Thus, the probability of examination and the length of exclusion determines the expected punishment. We derive a condition depending on these punishment parameters, which ensures that each bank reports truthfully in each period. Unfortunately, this condition cannot be satisfied for some range of the parameter values, indicating that non-monetary punishment may prove insufficient to deter banks from misreporting. However, a numerical example suggests that by appropriate choice of the probability of examination and the length of exclusion, the data consortium can achieve truthful reporting, without compromising anonymity unreasonably. If a monetary punishment is in place, then even if the probability of examination goes to zero (or, equivalently, anonymity is maintained) sufficiently severe monetary punishment induces the banks to report truthfully. Hence, a properly set monetary fine may ensure truthful reporting without violating anonymity. Moreover, the fine is never imposed, because the threat of having to pay it deters banks from misreporting.

Since anonimity is a key issue in this paper, some remarks are in order. Financial supervisory bodies (like the FSA in the UK or Bafin in Germany, etc.) have the information and competence to check the internal processes of banks related to operational risk, but data consortia are not subject to financial supervision *de jure*. However *de facto*, latent supervisory control already takes place in some cases. For example, at DIPO (the database of the Italian Banking Association), the custodian knows which member has sent an event, so the custodian knows which bank suffered that loss. As is apparent from the functioning of DIPO, they do whatever they can in terms of devices and internal procedure to guarantee anonimity in the bank-to-bank and custodian-to-third parties relationships, but in the bank-to-custodian relationship anonymity is not a first-order issue. This is the consequence of mutual trust between the banks and the custodian. This trust also enables DIPO to exert some pressure on the banks to report properly, for instance by cross-checking reports with other databases. Thus, the loss of anonymity is used to enhance the performance of the database. Another form of control in the case of DIPO is that sometimes Banca d'Italia requests data from them and member banks know it. The fact that Banca d'Italia has potential access to the data reported to the consortium represents a strong moral suasion against misreporting Hence, the custodian may have some control and power to incentivize member banks to report properly.[4]

To our best knowledge, our paper is the first to study the conditions and incentives that ensure that banks report truthfully to an operational risk data consortium from a game-theoretical point of view. We hope that our results will help to set appropriate rules for new data consortia that are expected to come into being. For instance, the Russia Banking Advisory Project of the International Finance Corporation recommends the establishment of a data consortium in Russia (Burucs (2009)).

The paper is organized as follows. In the next section, we briefly review the literature. In section 3, we present the model with the one-shot game, while in section 4 we proceed to the analysis of the repeated game. Section 5 concludes.

2 Related literature

Operational risk is generally characterized as "substantially unhedgeable and possibly large enough to threaten the existence of affected institutions" (Cummins and Embrechts (2006)) as evidenced by losses that in some cases amounted to billions of dollars. Chernobai et al. (2009) find that there is a strong link between individual operational events and firm-specific covariates, whereas the macroeconomic environment has less effect. Although this finding suggests that operational risk is idiosyncratic, de Fontnouvelle et al. (2006) fail to reject the hypothesis that the loss severity distribution across similar institutions is the same; a reason which underpins the usefulness of external data. The main benefit of participating in a data consortium comes from the fact that it contributes to a better operational risk management, helping to avoid the massive value destruction that operational shocks may cause.

Generally, if negative information about the bank becomes publicly known, the value of the bank reacts adversely to such an event. This explains banks' reluctance to disclose unfavorable information. Even if a high level of anonymity is guaranteed, once the information leaves the bank, the bank cannot control it completely. In the case of operational risk data consortia, the reports are first handled by a data manager (or custodian) who represents the consortium. The data manager checks the quality of the data and carries out anonymization. In some cases, the data manager knows where the data come from (for example, DIPO), while in others it is not the case (e.g. ABA). Furthermore, the descriptions of the operational risk events may give hints about the identity of the reporting bank.[5] The data collection process and these descriptions are channels that potentially may lead to a leakage of information. Cummins et al. (2006) show a strong, statistically significant negative stock price reaction when operational losses become publicly known. Perry and de Fontnouvelle (2005)

[4] We are tremendously grateful to Claudia Pasquini from DIPO to share with us these details.

[5] Obviously, banks may be very careful about such descriptions and do not reveal any information about themselves, but in this case the informativeness and consequently the usefulness of the report may be reduced. The trade-off between usefulness and anonymity seems unavoidable.

find that market value declines one-for-one with operational losses caused by external events, and the fall is even greater in cases involving internal fraud. These findings have been confirmed by Gillet et al. (2010). Generally, sooner or later big operational losses make it to the press, so in principle there is no reason to misreport them. However, it may be an important decision when to reveal them and how to sweeten them. These considerations may lead to delayed and distorted reports. Note that both strategic and psychological forces may cause misreporting.

As regards economic theory, our study is related to the literature on repeated games (see, for instance, Mailath-Samuelson (2006)). Banks play an n-player prisoner's dilemma, since given truthful reporting of the other banks misreporting is always better than being truthful for a single iteration. Although banks cannot directly observe other banks' actions, through the payoffs they notice if there was misreporting, as it will become clear later from the details of the model. Without the possibility of identifying the misreporting bank, punishment imposed by individual banks is inefficient because it cannot be directed with certainty towards the untruthful bank, so it reduces social welfare. In these games of imperfect monitoring, intertemporal incentives are used to induce cooperation.[6]

To keep the analysis tractable, we maintain the possibility of punishment and suppose that there is a supervisor who has the right to examine the validity of reported data and to impose a punishment in an efficient way. We do not model the emergence of the supervisor who can be seen as an agent to whom members of the data consortium delegate monitoring, following the idea of Diamond (1984). Thus, the idea of supervisor, embodies the possibility to detect misreporting.

3 Model

There is a set of banks $N = \{1, 2, ..., n\}$ that establish a data consortium to improve their operational risk management. Suppose that $n > 2$ and that banks are *ex ante* identical.[7]

Assume that bank i is hit in period t by a shock that follows a Bernoulli distribution with unknown parameter $p_{i,t}$. The resulting loss is represented by $x_{i,t} \in \{0, 1\}$.[8] For simplicity, we assume that neither $p_{i,t}$, nor $x_{i,t}$ change over time, so we drop the time subscript. Suppose that p_i is drawn from some random distribution. Thus, in any period bank i suffers a shock of magnitude 1

[6] See chapter 12 in Mailath-Samuelson (2006) for games with imperfect monitoring.

[7] The least number of banks forming a data consortium that we know of is eleven (case of DAKOR, Germany). There is no required minimum number of institutions to form a data consortium; however, the representativeness with respect to operation does matter for banks and coverage in terms of market share is important as well. Small banks with less data may be keen to participate in data consortia, while bigger banks with large internal databases could be reluctant to do so.

[8] Assuming continuous shocks would make the analysis more cumbersome, without yielding new insights.

with probability p_i, and with complementary probability it suffers a shock of magnitude 0. Magnitude-1 losses can be thought of as the low frequency-high severity events, whereas magnitude-0 losses represent the high frequency-low severity events. Without any data-sharing arrangement, bank i expects a large shock with probability p_i and prepares optimally for operational risk management using this information. Note that if the distribution of p_i was degenerate, then data consortia would be redundant, because setting aside sufficient capital (determined by p_i) is the best a bank could do and additional information from other banks would be inneccesary. That is why we add uncertainty and assume that p_i is drawn from a random distribution. Useful data from the data consortium reduces uncertainty and allows to form more accurate expectations about p_i, that is the probability of the occurrence of a large shock in the next period.[9] As a member of a data consortium, a bank reports the shock that realized in period $t-1$ to the consortium. We denote the vector of the true shocks at period $t-1$ by $x_{t-1} = (x_{1,t-1}, .., x_{n,t-1})$. Let $\hat{x}_{i,t-1}$ denote the report made by bank i, while the vector of all reports is represented by $\hat{x}_{t-1} = (\hat{x}_{1,t-1}, .., \hat{x}_{n,t-1})$. Let $\hat{x}_{-i,t-1}$ represent the vector of reports of all the banks except for bank i. Based on the vector of reports, the data manager calculates the set of values $(f(\hat{x}_{t-1}))$ that banks use to improve operational risk management in period t. We do not model explicitly optimal operational risk management; rather, we simply suppose that using the true set of values (that is, $f(x_{t-1})$) banks are able to improve risk management, compared to the case without a data consortium. However, banks find the set of values given by the data manager to be useful only if the reports are of sufficiently good quality. Banks cannot verify the validity of reports when they receive $f(\hat{x}_{t-1})$. Nor can they see what the other banks report, hence they play a simultaneous-move game. Therefore, from a bank's perspective the main question is whether the other banks will report truthfully or not; and in the face of this belief it should decide how to report.[10]

3.1 Costs

To have access to the set of information computed by the data manager, a bank has to provide information about its own operational risk events. Providing reliable information complying with the high reporting standards required by the consortia is costly. The cost does not come from collecting the operational loss events, but from the tension that while each bank values true external data, no bank likes to give away information about losses. For instance, the unreasonable fear to share data on operational risk events reported by Rumsey (2011) may cause banks to perceive it costly to provide the required information. Thus, the cost may appear as psychological strain and mistrust. Compared to

[9] These assumptions do not attempt to capture reality literally, neither are they crucial for the main message of the paper. We use them only to complete our model and motivate theoretically why data consortia are important.

[10] We do not model entry into and exit from the consortium explicitly. Banks are assumed to be members of the consortium (automatic entry), and if a bank believes the data coming from the consortium to be unreliable, then it can choose to misreport as well (implicit exit).

the case when a bank receives the external data and does not have to give anything in exchange, having to report losses yields less utility.

We suppose that the cost of reporting magnitude-0 events is zero, whereas that of reporting magnitude-1 shocks is positive. Since banks are *ex ante* identical, the cost of reporting is uniform across them. Formally,

$$c(x_{i,t}) = \begin{cases} 0 \text{ if } x_{i,t} = 0 \\ \beta_c^t c \text{ if } x_{i,t} = 1 \end{cases}, \quad (1)$$

where $c > 0$ and $\beta_c \in [0,1]$. The binary nature of cost reflects the dual characteristic of operational loss events. High frequency-low impact events are accepted as normal consequences of banks' daily operation. Moreover, reporting these events does not entail much effort. However, if they become public, low frequency-high severity events impair market value seriously, as they signal a weak internal control environment (see Chernobai et al. (2009)), and banks may be more reluctant to report them, supposing higher (potentially psychological) cost of these events. The β_c^t term captures the effect that as time passes the cost may diminish when $\beta_c < 1$ $\beta_c = 1$ represents time-invariant costs.

3.2 Payoffs

Assume that the payoff of participating in a data consortium relates in an additive manner to the total payoff of the bank. As a consequence, banks report truthfully if the benefits outweigh the costs.

Without loss of generality, we normalize the benefits of knowing the true external data and managing properly next period's operational risks to 1 at $t = 0$, when the consortium is set up. If the external data is of low quality due to misreporting, then the benefit is $k < 1$. Similarly to the costs, we allow that benefits vary with time, but still assume that the benefits are uniform across banks. Formally,

$$b_{i,t} = \begin{cases} \beta_b^t \text{ if } \hat{x}_{-i,t} = x_{-i,t} \\ k\beta_b^t \text{ otherwise} \end{cases}. \quad (2)$$

We suppose that $\beta_b \in [0,1]$, reflecting that as time goes by, having more reliable data from the consortium is possibly of less additional value than at the beginning. We allow for the case that $\beta_c \neq \beta_b$, so the change in the costs and benefits may be different.[11] We assume that $c < 1$, so that at the beginning benefits outweigh costs and participation in a well-functioning consortium is useful.

As a consequence, a bank hit by a small shock reports truthfully and derives utility β_b^t from the information received if the other banks have reported truthfully. When hit by a large shock, upon truthful reporting bank i's payoff has the following form:

$$\pi_{i,t}(f(\hat{x}_t), c \mid x_{i,t} = 1; \hat{x}_{i,t} = x_{i,t}) = \begin{cases} \beta_b^t - \beta_c^t c \text{ if } \hat{x}_{-i,t} = x_{-i,t} \\ \beta_b^t k - \beta_c^t c \text{ otherwise.} \end{cases} \quad (3)$$

[11] We thank for an anonymous referee for suggesting time-varying costs and benefits.

Note that the operational shock does not appear explicitly in the payoffs. The payoff function takes into account if operational risk is properly managed with the help of external data (benefit of β_b^t) or if it is not (benefit of $\beta_b^t k$). We assume that $k < c$, so a bank prefers staying out of the data consortium to being a truthfully reporting member of a dysfunctional consortium.

A bank that misreports avoids the costs but enjoys the benefits of the data consortium only if the other banks report truthfully. Thus, the payoff is:

$$\pi_{i,t}(f(\hat{x}_t), c \mid x_{i,t} = 1; \hat{x}_{i,t} \neq x_{i,t}) = \begin{cases} \beta_b^t \text{ if } \hat{x}_{-i,t} = x_{-i,t} \\ 0 \text{ otherwise.} \end{cases} . \tag{4}$$

If banks misreport generally, then they receive zero payoff, which can be seen as equivalent to the breakdown of the consortium.

Note that our payoffs are simplified and focus on the current period. However, the most recent data in data consortia are often incomplete and unreliable, and it takes some time until trustworthy and solid data emerge. Then period in our model can be interpreted as the latest time interval for which good and reliable data are available.

To fix ideas, consider Table 1 where tr stands for truthful reporting and m denotes misreporting. Suppose that the row player is bank i, while the column player represents the rest of the banks. For the sake of simplicity, assume that the rest of the banks use a coordination device, so they act in the same way and $\beta_b = \beta_c = 1$. Therefore, the payoff of the column player is that of a representative bank of the rest of banks.[12]

	tr	m
tr	$1-c, 1-c$	$k-c, 1$
m	1, $k-c$	0,0

Table 1. Normal-form representation of the reporting game

First, we analyze the stage game, which is a simultaneous-move game. Banks report their losses without knowing what the other banks report. Thus, banks cannot condition their report on observable reports made by other banks. We focus on pure strategy equilibria. The strategy of bank i in any period is to be truthful (denoted as tr) or to misreport (denoted as m). Thus, $s_i = \{tr, m\}$ for $i \in N$. Being truthful means that the report made by bank i ($\hat{x}_i$) is equal to the realization of the shock ($\hat{x}_i = x_i$). Misreporting implies the opposite.

The optimal action of any of those banks depends on what it believes about the truthfulness of the other banks' report. The payoff matrix is symmetric for each bank, with the cost depending on the realized shock. Since $k < c$, we have a prisoner's dilemma with unique Nash equilibrium predicting that both players will misreport. We consider symmetric equilibria, so given the dominant strategy of banks hit by the large shock, in the unique outcome of

[12] Since our perspective is that of a bank and we want to understand when a bank may decide to misreport, this simplification seems reasonable.

the game all banks hit by magnitude-1 shock will misreport. Banks anticipating this behavior will not find the set of information provided by the consortium to be useful, so they will not value being a member of it.[13] Our first result shows that misreporting is predicted to be the observed behavior.

Proposition 1 *In the one-shot game, misreporting is the dominant strategy.*

Proof. As regards the truthfulness of the other banks, two cases matter: (1) each of the other banks is believed to be truthful ($\hat{x}_{-i,t} = x_{-i,t}$); (2) there is at least one other bank that is not truthful ($\hat{x}_{-i,t} \neq x_{-i,t}$). In the first case, truthful reporting yields $1 - c$, whereas misreporting results in a payoff of 1. Therefore, misreporting is the best response. In the second case, if bank i misreports, then its payoff will be 0, while truthful reporting will yield $k - c < 0$. Hence, again, misreporting is the best response. As a consequence, independently of what the other banks do, misreporting is the optimal action, so it is the dominant strategy. ■

4 Repeated game

It is natural to consider data-sharing as an infinitely repeated arrangement, since it is not defined over a fixed horizon. Suppose that banks use a common, time-invariant discount factor, $\delta \in (0, 1)$. The discount factor is an exogenous characteristic of the banks and of the economic environment in general in which they operate. Data consortia cannot affect this variable. In a stable environment, banks plan over a long horizon and their discount factor is generally high. Less stable environments with a high turnover of banks may imply a lower discount factor.

The payoffs are the same as in the stage game. If all banks report truthfully in period t, then bank i's payoff will be $\beta_b^t - \beta_c^t c$ when hit by a large shock (that happens with probability $p_{i,t}$) and it will be β_b^t when suffering a shock of magnitude 0. The expected discounted value of the payoffs assuming that all banks report truthfully in each period is given by:

[13] If truthful reporting were not costly ($c = 0$), banks would have no incentive to misreport. This is the case because even though all the other banks misreport, no cost is incurred by reporting truthfully. This is the ideal case, when the data consortium works properly and banks do not perceive reporting costly in any sense. Then fears of loss of confidentiality will not distort reporting and all member banks will enjoy the benefits of the database.

$$
\begin{aligned}
E(T) = E(\sum_{t=0}^{\infty}\delta^t \pi_{i,t}) = \sum_{t=0}^{\infty}\delta^t E(\pi_{i,t}) = \\
= \sum_{t=0}^{\infty}\delta^t \left[E(p_{i,t})(\beta_b^t - \beta_c^t c) + (1 - E(p_{i,t}))\beta_b^t\right] = \\
= \sum_{t=0}^{\infty}\delta^t\beta_b^t - E(p_{i,t})c\sum_{t=0}^{\infty}\delta^t\beta_c^t = \\
= \frac{1}{1-\delta\beta_b} - \frac{pc}{1-\delta\beta_c},
\end{aligned}
\tag{5}
$$

where $E()$ is the expectation operator.

The main aim of our paper is to analyze the incentives to begin to report untruthfully. We start assuming that the data consortium works appropriately and all banks report truthfully. We compare the benefits that a well-functioning consortium yields to its members to the incentives to start misreporting, and derive our results based on this kind of comparison. For a consortium with already compromised data, the benefits of being a member are lower, so members will have less to lose if they misreport. Consequently, banks in such environments may find it advantageous to start misreporting earlier.

4.1 Decentralized case

First, we examine the decentralized case when there is no external supervisor, so misreports cannot be detected. In this setup, actions are unobservable, but banks are assumed to observe own stage payoffs ($\pi_{i,t}$). Therefore, the bank is able to notice perfectly through the own payoff if misreporting has occurred. The idea behind this assumption is that banks are able to evaluate whether participation in a data consortium is beneficial or not.[14] How can a bank notice if other banks misreport? Suppose that several banks are affected by the same OR event (e.g. series of fraudulent bank card transactions) and these events are publicly known. If in the data provided by the consortium the incidence of these OR events is missing or is perceived to be underreported, then a bank may have the impression that misreporting has happened. If a single bank can be identified as misreporting, then that bank can be sanctioned without any difficulty. In this section, we focus on the case where this identification is not possible.

In real life it is more plausible to assume that misreportings are noticed with some delay. Let $D \in \{0, 1, 2, ..\}$ denote the delays in detecting that misreports have occurred. Let $h_{i,t-1} \in H_{i,t-1}$ stand for the history of payoffs of bank i up to period $t-1$ where $H_{i,t-1}$ represents the set of all possible histories.

[14] For our purposes, it is enough to assume that the banks' beliefs about misreporting is correlated with the actual decisions. However, our strong assumption simplifies the analysis. Without it, we would need to specify a mechanism through which banks (stochastically) notice that misreporting has occurred.

Thus, $h_{i,t-1} = (\pi_{i,1}, \pi_{i,2}, ..\pi_{i,t-1})$. Strategy for bank i in the repeated game is a sequence of maps from possible histories to actions: $s_{i,t} : H_{i,t-1} \to \{tr, m\}$ for $t = 0, 1, 2, ...\infty$. For convenience, we denote by $H^{tr}_{i,t-1}$ the set of truthful histories, representing histories that no misreport has occurred reveal that up to period $t-1$.

Efficient punishment is only possible if the misreporting bank can be identified. An inefficient way of sanction is when a bank that notices that misreporting has occured, starts misreporting as well. Despite the lack of efficient punishment, truthful reporting is achievable, even though it is not a unique equilibrium.

Proposition 2 *In the infinitely repeated setup and decentralized case, the game has multiple Nash equilibria under some conditions.*

Proof. In general, in repeated games a large number of equilibria may be constructed. We construct just two (one leading to truthful reporting, the other to general misreporting) to show that truthful reporting is not uniquely implementable.

On the one hand, the strategy profile of misreporting in each period upon observing any history constitutes a Nash equilibrium, since there is no profitable unilateral deviation. Given that all other banks misreport, the best response is to misreport as well. Hence, $(s_{i,t} = m)_{i \in N}$ in any period is a Nash equilibrium.

On the other hand, the grim trigger strategy profile may induce truthful reporting by each bank in each period. Consider the grim trigger strategy of reporting truthfully in the first period, continuing to do so until the first misreporting is detected, after which misreporting ensues forever. If $D = 0$, then misreporting is detected immediately, but by allowing for $D > 0$, we take into account that misreporting can go on for a while. Bank i starts reporting truthfully, but when a misreport is noticed through the payoff, then bank i starts misreporting as well. Formally,

$$s_{i,t} = \begin{cases} tr \text{ if } h_{i,t-D} \in H^{tr}_{i,t-D} \\ m \text{ otherwise.} \end{cases}$$

and assume $h_{i,0} \in H^{tr}_{i,0}$. Note that we take into account the delay in $h_{i,t-D} \in H^{tr}_{i,t-D}$. This grim trigger strategy may conduce to cooperation if deviation does not pay off. Suppose that up to period τ no misreporting has occurred, but at this stage a magnitude-1 shock hits bank i and the bank decides to misreport. Then bank i has a gain of earning β^t_b instead of $\beta^t_b - \beta^t_c c$ through periods $t = \{\tau, ..\tau + D\}$, but this gain is followed by an infinite stream of zero payoffs, since no bank reports truthfully thereafter. Thus, the discounted value of payoffs resulting from the deviation is $\sum_{t=\tau}^{\tau+D} \delta^t \beta^t_b$. Alternatively, by reporting truthfully (and provided that all other banks do so in the future), bank i would enjoy the expected payoff given by (5). Therefore, if

$$\sum_{t=\tau}^{\tau+D} \delta^t \beta_b^t \leq \sum_{t=\tau}^{\infty} \delta^t \left[\beta_b^t - E(p_{i,t}) c \beta_c^t\right], \tag{6}$$

then no bank has an incentive to deviate from truthful reporting. Straightforward algebra yields that the previous condition is equivalent to

$$\frac{1-\delta\beta_b}{1-\delta\beta_c} < \frac{\delta^{D+1}}{pc} \frac{\beta_b^{\tau+D+1}}{\beta_c^{\tau}} \tag{7}$$

Thus, the grim trigger strategy leads to truthful reporting by each bank in each period. ■

While the previous condition (7) seems complicated, suppose for simplicity that $\tau = 0, D = 0$ and $\beta_b = \beta_c = \beta$. That is, the bank that misreports starts to do so at $t = 0$ and misreporting is noticed through payoffs immediately. Moreover, the benefits and costs of truthful reporting lose value with time at the same rate.[15] In this case, the condition boils down to

$$c \leq \frac{\delta\beta}{p},$$

where $p = E(p_{i,t})$. This simple condition indicates that when the cost of truthful reporting is low enough compared to the ratio of the discounting terms and the probability of big losses, then strategies like the grim trigger may sustain the good equilibrium of truthful reporting. Thus, compared to the one-shot case repeated interaction helps, since truthful reporting becomes a possible outcome, but not the unique one. The result also shows that cooperation is possible due to the potential loss of future benefits which can be seen as an implicit punishment for misreporting. This reasoning suggests that truthful reporting can be achieved if punishment is made in a more efficient way. Punishment cannot be efficient if misreporting is noticed or detected with a long delay. In condition (7), as D becomes large ($D \to \infty$), the inequality cannot hold.

The result also explains that a data consortium may work properly even in the absence of well-defined sanctions if member banks follow strict reporting norms as symbolized by the grim trigger strategy.[16] In fact, the lack of published evidence about banks' misreporting their operational risk events suggests that these data consortia contain good quality data, although publicly available membership documents only require that banks do their best when reporting without specifying sanctions if misreporting is detected. For instance, the participation agreement of the data consortium GOLD (UK) puts "Participants

[15] Note that if $\beta_b < \beta_c$, then the benefits gained from consortium data decrease more quickly than the costs, and if a bank misreports, then it maximizes the potential gains by doing so at $t = 0$. The same holds for $\beta_b = \beta_c$, since due to time discounting, the biggest gains of misreporting accrue for low values of t. Hence, misreporting at $t = 0$ can be easily rationalized.

[16] There are studies (both theoretical and experimental) showing why agents may be averse to break norms. See, for instance, López-Pérez (2008).

... commit to provide loss event data to the best of their institutional ability", but does not hold out the prospect of any punishment for banks that do not do so.[17] According to the previous result, if banks adhere to the norm of truthful reporting, then it becomes the unique outcome. Proposition 2, however, also suggests that if there is no chance to detect misreports ($D \rightarrow \infty$), then there may be equilibria leading to the breakdown of the data consortium.

4.2 Supervisor

In the last subsection we argued that if banks follow high-standard reporting norms, then this internal driving force is enough to make data consortia work appropriately. However, if such norms are not part of banks' behavior due to whatever reason (e.g. fear of losing confidentiality, general low level of trust in a country, generalized opportunistic behavior, etc.), then we cannot expect data consortia to function properly in a decentralized way, and an external device may be needed to enforce truthful reporting. We assume in this subsection that banks do not use grim trigger strategies. They do not punish by misreporting themselves.

In this section, we introduce a supervisor that has a double role: i) to validate the reported data with some probability and ii) to impose a punishment upon detecting that a bank misreports. Let $q \in [0, 1]$ be the probability with which the supervisor examines a given bank in any period. Hence, the expected number of periods until being checked is $\frac{1}{q}$.

When hit by a magnitude-1 shock and given that the other banks report truthfully, in period τ a bank that misreports obtains a payoff β_b^τ instead of $\beta_b^\tau - \beta_c^\tau c$. Since truthfulness is not observable, a bank can go on misreporting until it is detected. A bank misreports only when hit by a large shock, and possibly the supervisor examines it when suffering a small shock. Therefore, in expected terms a bank that misreports when being hit by a large shock is detected after $\frac{1}{qp}$ periods. The present value of the expected total payoff of misreporting (and supposing that all other banks report truthfully) evaluated at period τ is

$$E(M) = \sum_{t=\tau}^{\tau+\frac{1}{qp}} \beta_b^t \delta^t = \frac{1 - (\beta_b \delta)^{\frac{1}{qp}}}{1 - \beta_b \delta}. \tag{8}$$

Note that the above expected total payoff is the maximum gain from misreporting since it supposes that no other bank misreports. We consider two possible punishments: a non-monetary one and a monetary lump-sum fine.

The first consists of exclusion from the data consortium for a given number of periods (z) and it can be seen as a stigma. Other banks will not be willing to cooperate with the excluded bank in the case of other data exchange initiatives or other type of banking interactions.[18] Unfortunately, data consortia do

[17] The participation agreement is available on the Internet at www.bba.org.uk/content/1/c4/65/05/GOLD_Brochure.pdf).

[18] This punishment is a kind of temporary ostracism. Hirshleifer and Rasmusen (1989)

not disclose their full policy on operations, so we cannot give well-documented examples of exclusions. However, there is anecdotal evidence that in the case of detection of misreporting (or lack of reporting) the membership of the institution might be suspended, and the suspension might be canceled if there is a backward looking upload of past data. We note also that alternative sanctions based on exclusion are also possible. A stricter form of punishment would be if the bank that is excluded from the consortium would never receive the data for the periods of exclusion.

The second punishment implies monetary fine imposed on the misreporting bank. We are not aware of monetary punishment in data consortia, but given that monetary sanctions are a very common form in other areas, we thought it worthwhile to consider this alternative as well.

4.2.1 Non-monetary punishment

If a bank is found to have misreported, then it is excluded from the consortium for z periods. After the exclusion, the bank is readmitted and benefits from using the external data. Hence, the exclusion entails payoffs of zero during z periods, so the discounted total payoff during the punishment is $P^{nm} = 0$.

Using the previous expected discounted payoffs, we obtain the following result:

Proposition 3 *If*

$$c < \frac{(1-\delta\beta_c)\left[\delta^{\frac{1}{qp}}(\beta_b - \delta^{z+1})\right]}{p(1-\delta\beta_b)(1-\delta^{\frac{1}{qp}+z+1})} \tag{9}$$

holds, then each bank reports truthfully in each period.

Proof. A bank reports truthfully in the current period if and only if

$$E(M) + \delta^{\frac{1}{qp}} P^{nm} + \delta^{(\frac{1}{qp}+z+1)} E(T) < E(T). \tag{10}$$

The expression compares the expected discounted payoffs of misreporting and truthful reporting. The left-hand side has the expected discounted payoffs of misreporting that consist of the expected discounted payoff of misreporting during $\frac{1}{qp}$ periods, followed by the discounted (zero) payoff of z periods of exclusion and after $\frac{1}{pq} + z$ periods the expected discounted payoffs of being member of the data consortium again. On the right-hand side, the expected discounted payoff of a truthfully reporting bank is presented. Straightforward algebra yields that (10) is equivalent to (9). ■

The proposition says that if the cost of reporting truthfully is low enough given the parameters of the economic environment, then no bank will find it profitable to misreport. Consider the cost that equalizes both sides of (9). We call it the *threshold cost* since it makes a bank indifferent between being truthful

show theoretically how ostracizing noncooperators maintains cooperation. This finding is corroborated by experiments as well (see, for example, Cinyabuguma et al. (2005)).

or untruthful. An increase in this threshold cost can be interpreted as a gain the bank derives from a well-functioning consortium, since the threshold cost tells how large the cost (relative to the benefits) should be to eliminate the benefits from reporting truthfully.

The discount factor (δ), the depreciation factors of benefits and costs (β_b and β_c) and the expected value of the probability of large shocks (p) are exogenous to the data consortium. The discount and the depreciation factors may depend on country- and bank-specific conditions. For instance, in countries with a stable banking system, we expect δ to be higher than in countries with a volatile banking environment. In the same vein, older and well-established banks may exhibit a higher discount factor. The other two factors on the right-hand side of condition (9), that is, the probability of examination (q) and the length of exclusion (z), are choice variables of the data consortium. Partial derivatives indicate that the right-hand side of condition (9) increases both in the probability of examination (q) and in the length of exclusion (z). This points to the possibility of lowering the probability of examination to levels that do not deter banks from participating in the data consortium, while augmenting the length of exclusion to high levels, so that banks never find it optimal to misreport. Unfortunately, q and z cannot be chosen arbitrarily if condition (9) is to be satisfied. Moreover, for some parameter values condition (9) cannot be met at all, as shown by the following proposition.

Proposition 4 *If truthful reporting is to be uniquely implemented, the probability of examination cannot be kept arbitrarily low. There may be a range of costs* ($c \in \left[\frac{(1-\delta\beta_c)\beta_b\delta^{\frac{1}{p}}}{p(1-\delta\beta_b)}, 1\right]$) *for which banks may find it optimal to misreport.*

Proof. Let $G(q,z) = \frac{(1-\delta\beta_c)\left[\delta^{\frac{1}{qp}}(\beta_b-\delta^{z+1})\right]}{p(1-\delta\beta_b)((1-\delta^{\frac{1}{qp}+z+1}))}$. $G(q,z)$ is a continuous function. Since $\lim_{q\to 0} G = 0$, for any given cost and length of exclusion there is a $0 < \hat{q}$, such that for $q < \hat{q}$ the relation $G(q,z) < c$ holds. Therefore, if the probability of examination is arbitrarily reduced, condition (9) is violated. As a consequence, truthful reporting cannot be uniquely achieved, proving the first part of the proposition. As regards the second part, even if banks are examined in each period ($q = 1$) and the highest (that is, infinite) punishment is imposed on misreporting banks ($z \to \infty$), for very high costs condition (9) cannot be met. This is the case because $\lim_{q\to 1, z\to\infty} G = \frac{(1-\delta\beta_c)\beta_b\delta^{\frac{1}{p}}}{p(1-\delta\beta_b)}$ that may be less than 1. For instance, if $\beta_c = \beta_b$, then the limit equals $\frac{\beta_b\delta^{\frac{1}{p}}}{p}$, which for high values of p is less than 1. ∎

The above result implies that data consortia may perform better in environments where i) the discount factor (δ) is higher; ii) the depreciation factor of benefits (β_b) is higher; and iii) the depreciation factor of costs (β_c) is lower, since in these cases, *ceteris paribus*, the range of costs for which banks may find it optimal to misreport diminishes, that is, truthful reporting is more likely to obtain.

The previous result also suggests that applying even the harshest sanctions (in the form of everlasting exclusion) alone is not enough to deter banks from misreporting in some environments. Note that our variable q can be interpreted as the effort that the consortium puts into controling quality, for instance, by checking data carefully or cross-checking losses with other databases. Proposition 4 highlights the importance of these activities as well. While in the above result we showed that the probability of examination (q) and the length of exclusion (z) cannot be chosen separately and arbitrarily so that truthful reporting is achieved, the next corollary establishes a condition regarding the *joint* choice of these variables that guarantees truthful reporting.

Corollary 1 *If q and z are chosen so that*

$$1-\left(\frac{1}{1-\delta\beta_b}-\frac{pc}{1-\delta\beta_c}\right)(1-\beta_b\delta) < \tag{11}$$
$$< \delta^{\frac{1}{qp}}\left(\beta_b^{\frac{1}{qp}}-\delta^{z+1}\left(\frac{1}{1-\delta\beta_b}-\frac{pc}{1-\delta\beta_c}\right)(1-\beta_b\delta)\right)$$

holds, then each bank reports truthfully in each period.

Proof. Consider condition (10) that implies truthful reporting. Note that $\beta_b, \beta_c, \delta, p, c$ are given by the environment, while q and z are the choice variables of the data consortium. By rearranging the condition to have all elements containing q or z on one side, we obtain condition (11). ■

This corollary determines a condition that the joint choice of the probability of examination (q) and the length of exclusion (z) should fulfill so that banks report truthfully. Overall, the message of this section is that though the existing data consortia seem to work properly, it is not evident that this should be the case for future data consortia. The careful mix of checking the data quality and the appropriate sanctions when reporting problems emerge may ensure that the data consortium works as desired.

A numerical example We consider a numerical example to see whether the previous result restricts considerably the possibilities that all banks reporting truthfully in each period be the unique equilibrium. We fix the discount factor, the depreciation factors of costs and benefits and the probability of large shocks ($\delta = 0.9$; $\beta_b = \beta_c = 1$; $p = 0.1$) and calculate the threshold cost as q and z vary. The probability of examinations goes from 0 to 1, while the length of exclusion ranges from 0 to 100. Figure 1 reveals that regarding the probability of examination the biggest changes in the threshold cost (and, consequently, in gains from being a member of a data consortium) accrue for relatively low values, since the slope is the highest in that region. An interpretation is that to foster the proper performance of a data consortium, the important thing is to give the impression that misreporting banks can be detected. It is not necessary that each bank be audited frequently; q can be kept low so that anonymity is not overly compromised. Banks should perceive that there is some positive (but not necessarily high) probability of being detected if they misreport. The case of DIPO as described in the Introduction can be considered an example.

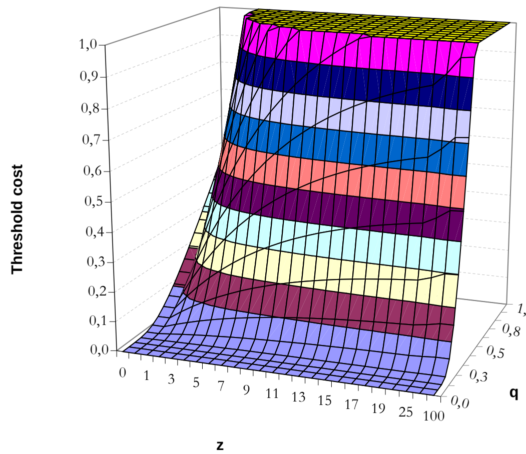

Figure 1: Threshold cost as z and q vary ($\delta = 0.9; p = 0,1$)

If we analyze jointly the increase in the length of exclusion and the probability of examination, then Figure 1 suggests that already for relatively low values of q a sufficiently long exclusion drives up considerably the threshold cost. Hence, if the data consortium is designed in a way that reflects these features, then it can be expected to work properly. However, it is worth mentioning that exclusion might cause additional problems on representativeness and may disturb time series analysis possibilities. Actually, we do not take exclusion literally, but as a proxy for stigma. A bank that misreports loses trustworthiness and other banks will not be willing to cooperate with it in any area. Hence, exclusion can be thought of as discipline imposed by the member banks.

4.2.2 Monetary punishment

If the supervisor catches a bank misreporting, it imposes a monetary fine of P^m. In the next period, the misreporting bank can participate in the data consortium as before. The next result shows that setting an appropriate monetary fine prevents misreporting.

Proposition 5 *If* $\frac{\delta - \beta_b^{\frac{1}{qp}}}{1-\beta_b \delta} + \frac{(1-\delta^{\frac{1}{qp}+1})pc}{\delta^{\frac{1}{qp}}(1-\delta\beta_c)} < P^m$*, then no bank finds it optimal to misreport in any period.*

Proof. A bank reports truthfully in the current period if and only if

$$E(M) - \delta^{\frac{1}{qp}} P^m + \delta^{(\frac{1}{qp}+1)} E(T) < E(T). \tag{12}$$

On the left-hand side we present the discounted payoffs of misreporting: $E(M)$ represents the expected discounted total payoff of misreporting, P^m stands for the monetary fine that a misreporting bank is expected to face after $\frac{1}{qp}$ periods and after the fine the bank enjoys again the benefits $(E(T))$ of belonging to a well-functioning data consortium. The right-hand side shows the discounted payoff of all banks reporting truthfully. Straightforward algebra yields the condition in the proposition. ■

The proposition tells that if member banks are willing to impose a sufficiently high fine on misreporting banks, then no bank misreports. To the best of our knowledge, data consortia do not impose monetary sanctions; compliance to truthful reporting is rather induced by non-monetary incentives. It may be due to the nature of data consortia, which is based on mutual sharing of reliable data. Participants may believe that monetary punishment would hamper the cooperation. If the sanction is seen as the price a bank pays for not reporting in accordance with the required standards, then monetary punishment may prove counterproductive, because an extrinsic price motivation crowds out the intrinsic motivation of cooperation.[19] However, in our setup the monetary punishment is set in a way that it is never used. It serves just as a deterrent, so in principal it should not affect cooperation negatively. In countries where non-monetary incentives do not work properly due to lack of trust or other reasons, applying fines may yield the desired deterrent effect.

5 Conclusion

In operational risk management, the increasing importance of external data coming from data consortia calls for studying the workings of these data-sharing arrangements. While most of the existing data consortia work adequately, we highlight the consequences of possible improper reporting that may be due to unjustified fear of confidentiality loss, mistrust and other reasons. Although empirical evidence on this issue is scarce, it seems important to study these problems, as more data consortia are desired and planned to be set up in countries where misreporting may become a concern.

Our model tries to capture these features: banks do not want to disclose operational losses, but would like to know the true operational losses of other banks to avoid them. We show that if misreports cannot be detected, then misreporting is the dominant strategy in a one-shot game and is a possible outcome in an infinitely repeated game. We also claim that strict reporting norms may lead to truthful reporting. In the absence of norms, we study the effect of an external device that we call supervisor. Uniqueness can be implemented if a supervisor has the right to check the validity of reported data. Even if anonymity is practically maintained (the probability of examination converging to zero), sufficiently severe monetary punishment induces banks to report truthfully. Non-monetary punishment in the form of temporary exclusion from the

[19] For this sort of arguments, see, for instance, Gneezy and Rustichini (2000) or Bénabou and Tirole (2003).

data consortium may achieve the same result under some conditions, although for some parameter values truthful reporting is not the unique possible outcome. Nonetheless, a numerical example suggests that even for small probabilities of examination that possibly do not deter banks from entering a data consortium, a sufficiently long exclusion enhances the benefits of data consortia, making them a successful data-sharing arrangement.

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