

1 ***Increase data sharing or die? An initial view for natural catastrophe insurance***

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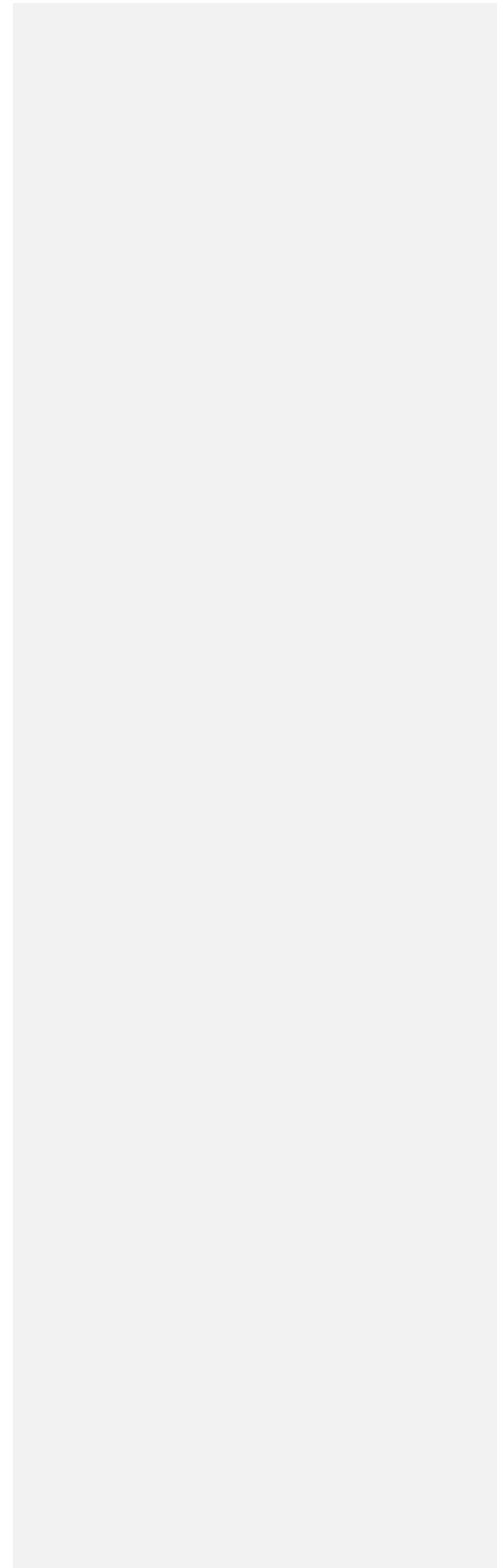
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20 **Abstract**

21

22 This article is an illustration of Geography in action, recounting an investigation into an industry's
23 views of data sharing. The insurance sector is fundamentally analytics driven and based on
24 geospatial data. One option for more effective and efficient insurance for natural hazard risks
25 (e.g. flooding, earthquake) is, in theory, to increase the sharing of data between the various
26 (re)insurance organisations. However, it remains unclear to what extent this is desirable or
27 practical for commercially sensitive data. This work creates a conceptual model of data sharing
28 in (re)insurance, focussing on loss (claims) data for natural hazards as an illustrative microcosm,
29 including barriers and solutions to sharing. In light of this, an initial view on the future shape of
30 insurance data sharing is given, finishing with an opinion on whether or not new external
31 disruptors (start-ups, tech giants - e.g. Google, Amazon, Tencent) pose an existential threat to
32 incumbent firms.

33



34 **1. Geography in action**

35 This article is designed to illuminate a real-world situation in which geography has been used,
36 focussing on the way the social science techniques used in geography can be deployed. The
37 multi-stage, iterative, collaborative process of investigation is deliberately laid bare to give you,
38 the reader, a sense of how research like this is conducted. The situation in question also involves
39 physical geography as it relates to insurance for natural hazards. Insurance is vital to the UK's
40 financial stability and resilience to weather-related extremes, and is a valuable element of the
41 UK's financial sector.

42

43 **2. Introduction**

44 As introduced in '*Natural Catastrophe Risk Management & Modelling*' (Mitchell-Wallace et al.,
45 2017), insurance is a financial mechanism designed to provide resilience to risks, including from
46 natural hazards such as flooding and earthquakes, by sharing (pooling) risk. All insurance
47 products (policies) are based on an insurer's view of how severe and likely a risk is, based on past
48 experience and/or additional numerical modelling. So, data driven analytics are fundamental to
49 the insurance sector, as evidenced by the existence of the actuarial profession (IFA, 2020).

50

51 Machine learning in the form of neural networks and other adaptive algorithms, sometimes
52 called Artificial Intelligence (AI), is becoming increasingly integrated into various aspects of the
53 (re)insurance industry (Balasubramanian et al., 2018; Bank of England, 2019; SCOR, 2018). With
54 this comes the spectre of a new generation of insurance providers (start-ups, tech giants) who
55 have significant data-handling expertise, and so might claim a share of the insurance market
56 (Catlin et al., 2017; Holland, 2019). Thus, an incentive exists for incumbents in the market to
57 consider sharing data more effectively between their individual organisations for mutual benefit
58 to mitigate this threat. However, ethical, regulatory, commercial and practical barriers are
59 believed to exist (Gunnar, 2011; ICO, 2018; KPMG, 2018; Minty, 2018). Consequently, the extent

60 to which data sharing is desirable or practical is currently under debate amongst established
61 players within the sector.

62

63 This research is a first attempt to capture in detail opinions from a range of stakeholders about
64 contemporary data sharing practice in the (re)insurance sector. By collecting these, and
65 contextualising them within experience of recent technology-driven changes in other sectors
66 (manufacturing, retail, banking), this study shines a light on the debate and strategic implications
67 for the insurance market.

68

69 **3. Experience from other sectors (i.e. opportunities)**

70 Recently the manufacturing (Du et al., 2012; Wiengarten et al., 2019), retail (Legner and
71 Schemm, 2008), and banking (Brodsky and Oakes, 2017) sectors have implemented strategic
72 initiatives at the level of the supply chain or market rather than the individual firm. This was
73 done to improve performance because each firm has fundamental limits on how it can improve
74 its operations, analytics and decision-making based only on its internal data and market
75 intelligence. It was facilitated by machine learning approaches, and required lots of 'big' data
76 (Gandomi and Haider, 2015).

77

78 Sharing data at the supply chain level can lead to significant operational and strategic benefits,
79 exemplified by Motorola's supply chain integration, which links partners in its manufacturing
80 supply chain to its financial systems (Blackman et al., 2013). This Motorola case demonstrates
81 clearly that this is not a zero-sum game; i.e. all partners benefit, rather than there being winners
82 and losers within the participating organisations. Indeed, many of the new strategies in
83 manufacturing such as Just-In-Time (JIT) and quality-control initiatives can only exist when there
84 is strong collaboration, trust and detailed data sharing between all members of the supply chain;
85 an example of this is Toyota's application of its 14 Management Principles (Liker, 2004).

86

87 In insurance, whilst data sharing is already widespread, there may be significant opportunities to
88 implement new data sharing projects in order to reduce the administrative cost structure, build
89 better analytics systems and to create new business models through strategic innovation
90 (Holland, 2019).

91

92 **4. Data types relevant to (re)insurance**

93 In this study, the focus is on natural catastrophe risk and thus four main categories of data;
94 exposure, environmental hazard, vulnerability, and loss (claims). These are typically integrated in
95 tailored GIS software tools called Catastrophe Models (Mitchell-Wallace et al., 2017). Insurance
96 products (policies) are designed using these GIS tools to estimate likely losses. *Exposure* data are
97 the assets at risk (e.g. houses), which the tools associate with a constructed understanding of
98 how these assets suffer in response to *hazards*, created by using claims (*loss*) data or modelling.
99 Specifically, the derived data that create numerical functions bridging between hazard and loss
100 are called *vulnerability*. In addition analytics may be augmented by other, externally derived
101 data to enhance understanding of the environmental process that drive hazards; illustratively, if
102 earthquakes (Parsons, 2004), European windstorms (Hillier and Dixon, 2020), or tropical cyclones
103 (Lloyd's, 2016; Steptoe et al., 2017) are better understood then better decisions can be made
104 about insuring for them.

105

106 Exposure data represent the assets to be modelled (assets at risk). Typically, this includes a
107 building's value and characteristics (roof type), geographic location, and details of insurance
108 financial structure (such as deductibles and limits). Environmental hazard data are any form of
109 data used to build a picture of hazard (e.g. stochastic event sets) or otherwise enhance risk
110 estimates for natural catastrophes. These data might be from global climate models (GCMs).

111 Loss data are any form of data related to a claim for which loss has occurred, perhaps during a
112 storm. These come in two broad classes:

- 113 • *Detailed data* are information relating to an individual policy and insured asset, and might
114 be thought of as 'house-by-house' data.
- 115 • *Aggregated data* are data grouped into a total amount by some criteria, perhaps across a
116 set of insurance policy holders in a geographic region within time-window or hazardous
117 event.

118

119 **5. Targeting the research**

120 There are many types of data shared across the insurance sector, for a variety of reasons. This
121 study focuses specifically on the sharing of loss data related to natural hazards, either in detailed
122 (location specific) or in aggregate form. Loss data are a useful illustrative microcosm since this
123 type of data is generally perceived as highly-sensitive and thus hard to share. Barriers against
124 the sharing of claims data should therefore be readily evident whilst still representative of those
125 affecting exposure data, and thus also vulnerability as it is a derivative of these two types.
126 Environment science data pertaining primarily to hazard are a different case, where vast
127 quantities of *raw* data are already freely available if non-trivial to use (CDS, 2020; Editorial, 2016;
128 Popkin, 2019; Thornley and Claghan, 2019) and the opportunity firms have to differentiate
129 themselves is by the analytics and the derived data products they can produce internally. It is
130 possible that this is where other data landscapes will move to.

131

132 **6. Study design**

133 The overarching aim of the study was to gain insights into whether or not existing (incumbent)
134 firms in the (re)insurance sector should increase data sharing. In order to achieve this, a diversity
135 of views was collected relating to the following questions:

- 136 ▪ How are data shared already and, if so, why?
- 137 ▪ Is sharing loss data difficult, and what are the main barriers to sharing?
- 138 ▪ What might some solutions be, now and in future?

139 A two-phase approach was adopted, iteratively working with insurance practitioners to develop
140 insights using data collection methods designed to engage efficiently with these busy
141 professionals who have little time to spare.

142

143 *6.1 Phase A: Brief interviews at conferences*

144 There are a range of archetypal roles within the (re)insurance sector, ranging from the primary
145 insurer who sells policies to parties who want insurance, to 'Commercial Modellers' who design
146 catastrophe models. Any one organisation (e.g. SwissRe, Willis Towers Watson, AIR, Bank of
147 England, Zurich Plc.), may undertake one or a few of these roles, and may share catastrophe-
148 related loss data in detail or in aggregate with other organisation. As a basis for discussion a
149 conceptual model, presented as a diagram (**Fig. 1**), was created by co-author Hillier from a
150 catastrophe modelling textbook (Mitchell-Wallace et al., 2017) and his experience working in
151 (2008-2010) and with (2010-) the insurance sector. Similarly, initial mind-maps about barriers
152 and solutions to data sharing were created. As a starting point, Phase A sought views on

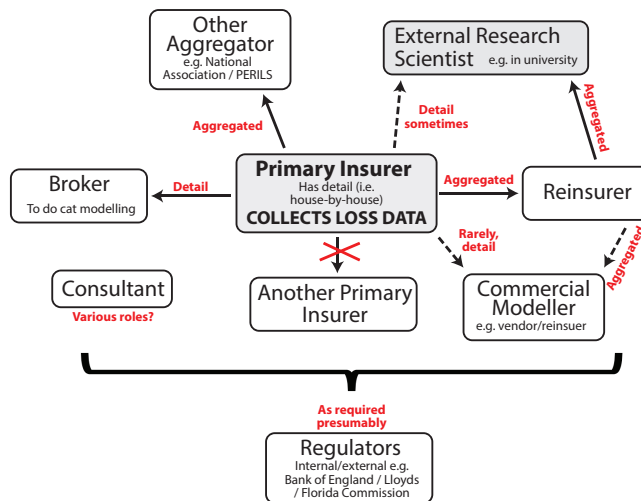
- 153 • the conceptual model (**Fig. 1**)
- 154 • barriers and solutions to data sharing with university-based scientists. (**Fig. 2**)

155

156 In total, 26 industry practitioners and 22 academics participated. Only individuals who self-
157 assessed as 'having enough experience to form a view' participated. All talked individually for 2-
158 10 mins with Hillier, also marking their views on an A0 poster. The participants annotated the
159 conceptual model and, for the partially-filled mind-maps provided, added up to 3 dots to indicate
160 which of the options they believed (in their experience) were most significant barriers/solutions

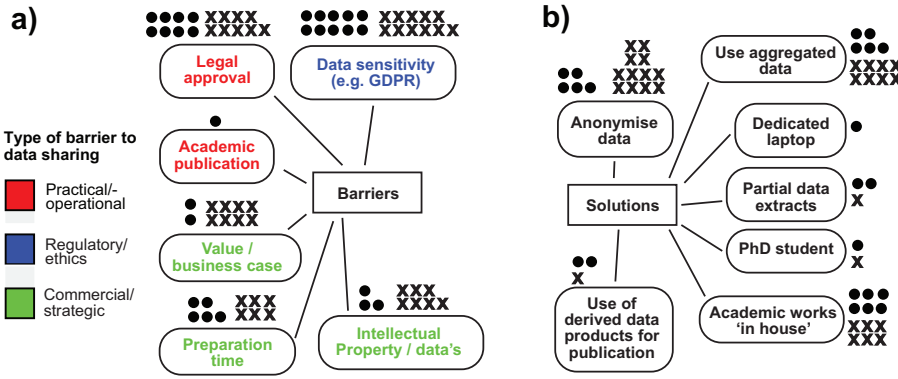
161 to the sharing of loss data with academics. Empty space was available, and participants were
 162 encouraged to add alternative barriers to the mind map, but suggestions were sufficiently similar
 163 to existing options that they were merged for analysis. Participants were asked to assume a good
 164 inter-personal relationship between academic and insurer, although this is a non-trivial
 165 prerequisite (Hillier et al., 2018). The interviews were conducted during poster sessions, or tea-
 166 breaks, at events that the participants were already attending so the time cost to them was
 167 minimal.

168
 169 The three conferences were attended in 2019, and all had a mixture of academics and
 170 practitioners attending: (1) The General Assembly of the EGU (European Geosciences Union),
 171 11th April 2019; (2) 9th Annual Conference of the IRDR (Institute for Risk and Disaster Reduction)
 172 at University College London, 19th June 2019; (3) TECHNGI Conference on AI & Next Generation
 173 Insurance Services at Willis Towers Watson in London, 26th November 2019. No information was
 174 carried over between conferences (new poster used), to minimize the influence of prior opinions
 175 on participants.



176
 177 **Fig. 1** - Model assessed in Phase A of how loss (claims) data are shared between the main
 178 organisational types within the (re)insurance industry and with academia.

179



180

181 **Fig. 2** - Mind maps of (a) barriers and (b) solutions to sharing loss (claims) data sharing with
 182 academics. Dots and crosses are votes for the most significant of these, from industry
 183 practitioners and academics respectively. Barriers are categorised and colour coded accordingly
 184 - see Section 6.2.

185

186 *6.2 Phase B: Online survey*

187 In order to test the robustness of the conceptual model, and refine it further if necessary, an
 188 online survey was conducted, wherein respondents were asked to evaluate the model as revised
 189 after Phase A (**Fig. 3**). An online survey was made necessary by COVID-19. It was co-designed,
 190 with input from Willis Towers Watson, a (re)insurance broker with a research network, and four
 191 themes were investigated:

- 192 1. The value of sharing data in the insurance value chain
- 193 2. On how loss data are currently shared between archetypal (re)insurance roles
- 194 3. Strategies and mechanisms to make data sharing more effective
- 195 4. Visions of the future of data sharing in (re)insurance

196 These place the model of current data sharing into a wider context and help to shape an initial
 197 view of its implications. Phase B targeted 22 participants to provide viewpoints that together
 198 cover a spectrum of practitioner perspectives from across the industry, and is fully described in a
 199 report aimed at (re)insurance practitioners (Hillier et al., 2020). Reference will be made to the

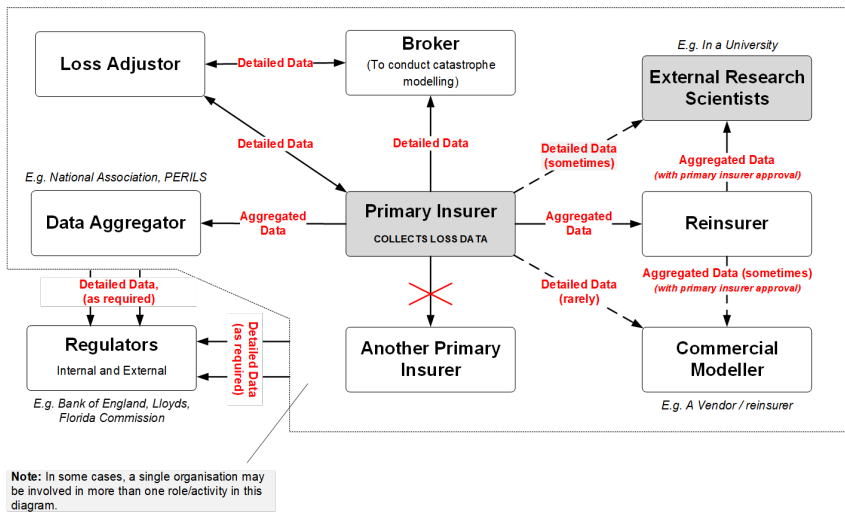
200 headline results of other elements, but theme 2 is the primary focus in this paper. Respondents
 201 were asked if they agreed with the statement "The diagram (Fig. 3) accurately captures how loss
 202 data is currently shared in the insurance sector", and to make comments about the accuracy of
 203 the diagram.

204

205 **6.3 Ethics**

206 Data collected at the conferences and in the survey were undertaken in accordance with good
 207 practice, and clearance was given in accord with Loughborough University's ethics process.

208



209

210 **Fig. 3** - Model assessed in Phase B of how loss (claims) data are shared between the main
 211 archetypal functional roles within the (re)insurance industry, and with academia.

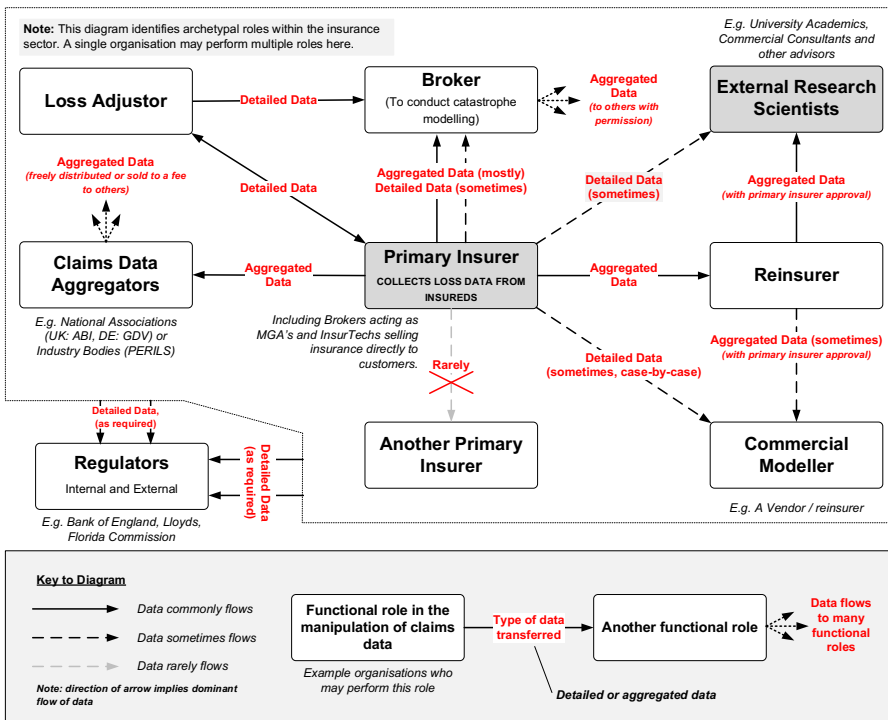
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213 **7. Results**

214 **7.1 Existing loss data sharing within (re)insurance**

215 The primary, overarching feature of the conceptual model (Figs. 1,3) is that it is deliberately and
 216 explicitly centred around the source of data, defined as a 'primary insurer' who directly interacts

217 with the insured in event of a loss. The second critical feature is the presence of arrows
 218 indicating data flow between organisations. Importantly, no interviewee in Phase A disagreed
 219 with these assertions, and in Phase B the perspective of the survey respondents is encapsulated
 220 in a comment: "it is an accurate depiction of a low-resolution picture". 76% of respondents
 221 agreed or strongly agreed that, as it purports to, the relationship diagram accurately depicted
 222 how claims data are shared between organisations in the (re)insurance industry. Only 19%
 223 disagreed, although numerous caveats about detail were suggested. No one strongly disagreed
 224 with the diagram, suggesting that any inaccuracies were tolerable.



226 **Fig. 4** - Final conceptual model of how loss (claims) data are shared between the main archetypal
 227 functional roles within the (re)insurance industry and associated organisations.

228
 229 **Fig. 4** is a revised model, with alterations based upon a synthesis of respondents' comments. For
 230 clarity, it very deliberately remains a simple descriptive model; upon attempting to add all

231 connections, the diagram became unreadable. For instance, because it is of claims data flowing
232 from insured parties, via a primary insurer, it does not emphasise the possibility of brokers acting
233 as intermediaries between the primary insurer and reinsurer. However, in response to
234 comments, a splay of arrows was included to indicate that brokers might share aggregated data
235 with a range of organisations, provided permission is given by the organisation supplying the
236 data to the broker. Exceptions and caveats that respondents identified, and are acknowledged
237 but not incorporated include:

- 238 • “The diagram is not taking treaty and binder policies into concern”.
- 239 • “[The diagram] does not reflect the variability with respect to types of product or line of
240 business (e.g. parametric versus indemnity, commercial property, household), nor the
241 data flows for catastrophe pools, mutuals, or special purpose vehicles. In addition,
242 products such as binders, facilities and other mechanisms”.
- 243 • “It’s important to consider different classes of business – e.g. property catastrophe
244 reinsurance is high quality - but many other areas less good”.
- 245 • “contractual understanding needs to be depicted where the loss chain is beyond the
246 simple insured-insurer-reinsurer chain”.

247

248 In **Fig. 4**, loss data are shown as only collected by the 'primary insurer' functional archetype
249 because this is defined in the model as the organisation in direct contact with the insured. Some
250 respondents identified the broker as an additional primary collection source if they are acting as
251 a Managing General Agent (MGA) for a primary insurer, however we consider a broker operating
252 in this capacity to be part of the primary insurer archetypal role. Similarly, some new InsurTech
253 firms may also be operating in this primary insurer archetypal role if they are providing insurance
254 directly to customers. In summary, practitioners confirm that (i) data flows radiate outwards

255 from a 'primary insurer' role and (ii) data do move between organisations if value in doing so can
256 be identified.

257

258 In the Phase B survey (Hillier *et al* 2020), eleven distinct benefits stemming from increased data
259 sharing are identified in responses that relate to customers (e.g. better understanding of risk),
260 society (e.g. reduced protection gaps), individual firms (e.g. operational efficiency), product
261 innovation and delivery (e.g. faster development), and market-wide (e.g. improved market
262 stability). Significant business advantages are clearly recognised, although these are typically
263 indirect or inferred outcomes of sharing rather than immediately tangible.

264

265 *7.2 Is sharing loss data difficult, and what are the main barriers to sharing?*

266

267 Phase A interviewees rated the difficulty of sharing both loss data and academically produced
268 environmental science data (e.g. outputs of GCMs). Environmental science data were chosen as
269 a reference as there is a strong drive to share such data freely and openly. A scale of 1-5 from
270 'very easy' to 'very hard' was used, and participants answered based upon their personal
271 experience. Overall, the sharing of environmental science data was rated easier than loss (claims)
272 data (2.47 vs 4.31, $p \ll 0.01$, 2-tailed). There was no significant difference when responses were
273 separated into academics and practitioners, and each conference produced the same pattern.
274 So, this explicitly confirms that there are barriers to loss data sharing.

275

276 What are these barriers? Options (**Fig. 2**) were classified into a typology, consistent with research
277 in other sectors (Kembro *et al.*, 2017): Non-optional factors based on ethics and/or regulation
278 such as GDPR (ICO, 2018); Commercial factors (e.g. IP, competition, lack of overarching common
279 goal between all participants, complexity of market structure) that have their origin in a
280 businesses' approach or strategy (Arunachalam *et al.*, 2018); practical barriers with operational,

281 technical or logistical origins (Kembro et al., 2017). In both Phase A (Fig. 2) and Phase B (Fig. 5),
 282 data sensitivity and the value (business case) for the activity rated highly. For collaboration with
 283 university-based scientists in Phase A, legal approval to send data to a very different (non-
 284 commercial) environment was seen as problematic, whilst for sharing with other insurance
 285 organisations in Phase B intellectual property was understandably a far more prevalent concern.
 286 Irrespective of detail, however, it is clear that barriers are recognised.

287



288

289 **Fig. 5** - Barriers identified in the survey (Phase B) having the greatest impact on data sharing
 290 within the insurance sector (Hillier et al., 2020).

291

292 *7.3 Potential solutions to improve data sharing*

293

294 When presented with the specific scenario of sharing loss data with a university-based scientist,
 295 Phase A participants identified a range of practical, operational-level solutions to overcome
 296 barriers (Fig. 2b), although they confirmed a long-term trusting relationship as a pre-requisite
 297 (Hillier et al., 2018). In addition to the pre-prepared solutions, legally mandated data sharing was
 298 noted as a means of eliminating these issues entirely, and a standard template for data sharing
 299 for use by legal departments was postulated as a mechanism to reduce friction in data
 300 movement. However, the three favoured solutions for sharing detailed (house-by-house) data
 301 between organisations have one key shared characteristic; essentially, they limit the movement
 302 of detailed loss data outside of the primary insurer. Either the data are degraded to make them

303 less sensitive (anonymise and aggregate), or work is *de facto* in house so that the data can be
304 viewed as never having moved. This echoes the reluctance for data to flow found above.

305

306 In Phase B (Hillier et al., 2020), to achieve multi-organisational benefits by sharing data as is done
307 in other sectors (manufacturing, retailing and banking) (Du et al., 2012; Wiengarten et al., 2019),
308 respondents were of the opinion that *Marketplace agreements*, i.e., sharing data in prescribed
309 format(s) in an electronic marketplace, will be the most significant mechanism for the insurance
310 sector in 3-5 years' time and expect a large increase in the usage of *Commonly agreed voluntary*
311 *standards* and *Open access data hubs*. In short, a change to a configuration where market
312 benefit outweighs the advantage of individual firms is anticipated. A common characteristic of
313 such initiatives is that, to succeed, they need to be trusted by the organisations providing the
314 data, and not seek competitive advantage in themselves. This 'trusted broker' concept
315 (Zarkadakis, 2020) also arose in the Phase A. Insurance bodies (e.g. Association of British
316 Insurers), academic set-ups (e.g. <https://www.cdrc.ac.uk/>), or commercial players (e.g. PERILS,
317 Oasis) could be well placed to serve these needs.

318

319 In terms of a vision for the future, on a 3-5 year time horizon, but not within 12 months,
320 respondents in Phase B (Hillier et al., 2020) expect that data sharing in (re)insurance will change
321 from the status quo, likely to a mix of three alternative operating models that are known in other
322 sectors: industry-wide electronic marketplaces (Malone et al., 1987); competing smart networks
323 (Van Heck and Vervest, 2007); or a new entrant (InsureTech start-up or tech giant) that could
324 transform the existing arrangements by offering insurance services using radically new business
325 models that exploit network economics, business peer-to-peer, and consumer peer-to-peer
326 arrangements, all supported by advanced AI and analytics capabilities (Catlin et al., 2017). It is
327 not clear which (if any) will dominate, though the participants favoured electronic marketplaces.

328

329 **8. Implication: Increased data sharing seems inevitable for natural hazard insurance**

330

331 The current sub-optimal flow of data (barriers), combined with existing technologies and
332 examples of more effective data handling in other sectors creates the opportunity for disruption
333 to the status quo in insurance (Catlin et al., 2017; Van Heck and Vervest, 2007). Currently, firms
334 in the archetypal 'primary insurer' role restrict data (exposure/loss) flows, and as the party at the
335 point closest to data capture have market power, but at a cost to the efficiency of the overall
336 market. Following other sectors, early technology developments have focused on defining
337 common technical standards for the exchange of data for standard processes (e.g. ACORD, Oasis
338 Open Data Protocol), however later-stage changes also reflect a change in the business patterns
339 such as shared *systems* (Holland et al., 2005) and smart business (Heck and Vervest, 2007). In
340 firms using blockchain/distributed ledger technology (Cognizant, 2020) there are signs of change
341 in (re)insurance despite the cultural challenges of apparently altruistic data sharing. So, change
342 seems likely either through more extensive use of existing mechanisms or by a more dramatic
343 paradigm shift, as discussed below.

344

345 Why is increased data sharing likely, or perhaps inevitable, within the part of the insurance
346 sector dealing with risk from natural hazards? While the attitude of interviewees demonstrated
347 that primary insurers are reluctant to allow data flow, it was also the attitude that solutions
348 could be found if a clear business benefit can be demonstrated. For example, outside the
349 context of university-based scientists, fraud prevention is an area where a clear and quantifiable
350 mutual benefit to all companies involved has been identified and data are now shared (Radford,
351 2019), e.g. the 'Claims Underwriting Exchange'.

352

353 The pressure for change in natural hazard risk can be understood by considering a fundamental
354 quirk of the insurance business – that correct risk pricing is the best strategy – and by analogy

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356 with recent changes in motor insurance (EIOPA, 2019). The need for an ecosystem of firms to
357 assess natural hazard risk (Fig. 4), and thus sharing between them, is directly a result of the scale
358 and complexity of natural hazard risks.

359

360 The quirk of insurance is that anything readily realisable that leads to better pricing is inevitable
361 in the scenario of a functional market. Pricing risk correctly (at least internally) is the route to
362 business success if other factors (e.g. firm management, marketing) are equal; under-price high
363 risks, and a firm loses money, over-price good (low) risks with respect to competitors and the
364 firm loses customers. Critically, better risk pricing only needs to be true for a small fraction of
365 the market initially for change to take hold. Consider 10% of a pool of customers have better
366 data, and risk pricing. If half of these are good risks, and can be offered a lower premium, they
367 will likely take it, and illustratively a small company offering these would tend to be successful.
368 This causes the level of risk, and thus average premium (offered to all) in the undifferentiated
369 remaining customers to rise. Then, more customers may be prepared to offer data. A convincing
370 recent example of this type of behaviour is telematics ('black boxes') in cars (e.g. Insurethebox).

371

372 For car insurance, all the analytics to translate data into pricing are readily done within one firm;
373 so, no sharing of data between organisations is forced. However, catastrophe risk for natural
374 hazards is much more difficult to assess (see Mitchell-Wallace *et al*, 2017). Not only is it based
375 upon a highly complex, non-linear and changing set of physical systems (atmospheric,

376 hydrological, etc.), it combines this with an interacting set of engineered human systems spread
377 across large spatial areas so that losses 'accumulate' (>10,000 things damaged at once) in a way
378 that motor accidents do not; this results in very large loss events (e.g. storms) that are also rare
379 and thus poorly observationally constrained. Given this complexity, no single firm is able to
380 undertake all aspects of the natural hazard risk assessment. Thus, it is not just the obtaining of
381 data (now actually of a number of types from a number of sources) but the sharing of it that will

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383 lead to effective and efficient pricing of risk. Placing this back in context of the initial assertion,
384 that whatever leads to better pricing of risk (if reasonably practical, given data availability,
385 analytical tools) is inevitable, it is clear why the advent of increasingly sophisticated and available
386 data, analytical tools (e.g. machine learning) along with clear examples of transformation in
387 other sectors (e.g. banking, retail) imply that increased data sharing for natural hazard risks is
388 rather likely and perhaps inevitable.

389

390 The caveat to this argument is a new entrant (e.g. Tech giant) capable of internalising all or most
391 of the current archetypal insurance functions needed to assess natural hazard risk, which would
392 render the concept of sharing obsolete.

393

394 **9. Conclusions**

395 This report illuminates and clarifies an emerging consensus amongst practitioners, rather than
396 generating a revelation to them, but is arguably more powerful for that. By brief interviews and
397 a survey, including 47 (re)insurance practitioners, a view is documented in which:

398

- 399 1. Currently, the flow of loss data is seen as radiating out from organisations with the
400 archetypal '*primary insurer*' function that tightly control it, with substantial barriers.
- 401 2. Significant business advantages are clearly recognised to data sharing between
402 organisations, but a transition to new mechanisms and models of working is typically
403 expected on a 3-5 year time-frame.

404

405 By combining these it can be concluded that this sub-optimal data flow and thus market
406 inefficiency presents a clear opportunity for disruption, especially when tools, technologies and
407 approaches to data handling are well-established and have substantially increased efficiency in
408 comparable sectors. What is not known is whether or not incumbent insurers will innovate

409 sufficiently rapidly to mitigate the threat of a new, disruptive entrant(s) in InsurTech or a tech
410 giant (e.g. Amazon, Google) acquiring a substantial share of the value within insurance related to
411 natural hazard risk. This '*innovator's dilemma*' is typical of markets in transition where
412 incumbents wish to maintain the status quo because embracing a new innovation is inherently
413 risky (Christensen, 1997). The study illustrates that, as geographers, we can contribute by
414 engaging positively with industry partners to co-create knowledge and insights.

415

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417

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423 Vivid Economics, Willis Towers Watson, World Bank.

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