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Susan Howick, Colin Eden

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Learning in disrupted projects: on the nature of corporate and personal learning

Susan Howick and Colin Eden

University of Strathclyde, 40 George Street, Glasgow G1 1QE, United Kingdom

Susan.howick@strath.ac.uk

For Peer Review Only

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3 **Abstract:** The majority of large, complex projects suffer disruptions. These can have
4 unexpected and significant impacts on a project, resulting in excessive time and cost
5 overruns. Disrupted projects therefore require careful management in order to minimise the
6 impact of a disruption. One element of a project for which disruptions will have a particular
7 impact is on any anticipated learning gains. Loss of learning from disruptions can often be
8 very significant. This lost learning may be from individual workers (personal) or by the
9 organisation (corporate). An understanding of the impact of a particular disruption on
10 learning is required to enable effective management of that disruption. This paper argues that
11 improved management of learning in disrupted projects may come from the disaggregation of
12 personal and corporate learning from the typically used aggregated learning curve
13 presumptions. The literature is reviewed to explore whether a method of disaggregation can
14 be determined from existing propositions about the behaviour of learning curves. The
15 explorations demonstrate that the disaggregation of a learning curve is complex. The
16 contribution of this paper derives from developing an understanding of the role of asymptotes
17 in constructing learning curves, and the nature of the interaction between personal and
18 corporate learning. These two aspects are argued to be crucial aspects in managing the
19 impact of disruptions on learning. The main motivation for this work is to provide managers
20 with an understanding of the disaggregation process, in order that they can think through the
21 impact of a disruption on learning in their own projects.
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51 Keywords: project management, production planning, repetitive manufacturing
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58 1. Introduction 59 60

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3 Cost and schedule overruns are very common in large, complex, projects (Morris and Hough
4 (1987)). A common cause of such overruns is the occurrence of disruptions and delays
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6 throughout the life of the project. A disruption is an event that precludes a project from being
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8 completed as planned and a delay involves the completion of the project being later than
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10 planned (Eden et al. 2000).
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17 Typical disruptions and delays that can occur on projects include a client requesting changes
18
19 in the product with significant consequences for rework (Cooper (March 1993)), delays
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21 occurring in the receipt of materials leading to the disruption of the work schedule as the
22
23 organisation works around the delays, requests to accelerate the project which leads to
24
25 rescheduling of tasks. The impacts of the disruptions are often systemic, creating complex
26
27 consequences for the project (Eden et al. (2000)).
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34 For projects that involve some form of repetitive task, such as the manufacture of multiple
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36 products, learning by workers is generally expected (Wright, 1936). If a project that
37
38 anticipates gains from learning is disrupted, then it is likely that the expected learning will be
39
40 impacted (Globerson et al. 1989; Shtub et al. 1993; Badiru 1994; Arzi and Shtub 1997; Ash
41
42 and Smith-Daniels 2004; Norfleet 2004). For example, one of the most common disruptions
43
44 to a project is the demand for a change by the customer. Whilst we are going to take design
45
46 changes as an example this is of course not the only category, other common examples in
47
48 relation to engineering projects are delayed receipt of materials, a slow client approval
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50 process or larger than expected comments being made on designs by the client. A change in
51
52 the design of a product may have the following impact on expected learning:
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57 New instructions are given to production workers – learning that was gained on
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59 previous tasks will be lost.
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Possible plant layout changes, for example an increase in the number of production stages – this will lead to workers having to relearn the scheduling of the tasks at each stage of production, and so learning on the previous scheduling will be lost.

New tooling to do the new work – any learning gained on the old tools may be lost and workers would then need to gain learning on the new tools.

Increase in the scope of work required - additional workers may be required and they will need to achieve learning to catch up with the current workers.

Additional rework - this increases the amount of work to be done, therefore the project will need to be accelerated if the organisation wishes to complete the project on time and hence this may involve bringing in additional workers.

Another example of a disruption during production is the delay in receipt of materials from the customer. This may cause production either being halted for a length of time or workers being transferred onto other tasks. Either of these cases may lead to workers forgetting what they were doing and hence taking longer to complete a task when they recommence the work. Another impact may be that, in attempting to keep to schedule, workers continue with tasks out of the planned order. This may lead to future rework that, as in the previous example, can also impact learning gains.

There are also important secondary effects to consider. When a disruption occurs that creates an expected delay to the project, then management may take actions in an attempt to

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3 accelerate the project (such as hiring additional workers, use of overtime, placing pressure on
4 workers). Although these actions are taken in an attempt to accelerate the project, knock-on
5 effects may occur which actually reduce productivity on the project (Cooper (March 1994);
6 Howick and Eden (2001)). For example, the use of overtime can lead to fatigue in workers, or
7 the use of excessive pressure can lead to a reduction in workers' morale. These, in turn, can
8 cause higher labour turnover on the project than expected, hence losing learning gained by
9 individual workers on the project. In addition, in coping with the knock-on effects of the
10 disruption, management may be side-tracked from planned actions and may not have time to
11 think about introducing expected or normal organizational/corporate learning such as the
12 introduction of new tools or the improvement of the layout of the plant.
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29 In this paper, we are interested in relatively short-run (say between 30 to 200 items) repetitive
30 manufacturing projects. When a disruption occurs on such a project, there are multiple
31 consequences for the project. As we have suggested above, this can include significant
32 consequences for any learning gains expected. In order for the impacts on the expected
33 learning to result in minimal impact on the overall time and cost of the project, the disruption
34 will need careful management. This paper explores the process of understanding the impact
35 of disruptions on those elements of the expected learning gains that need careful
36 management. The main motivation for this is to provide help to managers to support them in
37 thinking through the impact of disruptions on learning in their own projects.
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53 **2. Background to the Research**

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55 The authors are part of a team that has been involved in the analysis of the causes of cost and
56 time overruns on large and complex shipping, aerospace, transportation and engineering
57 projects. Over the last twelve years the team has been involved in the forensic analysis of ten
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3 projects (Ackermann et al, 1997). Each of the analyses was carried out as a part of litigation.
4
5 This provided the team with unique opportunities to carry our in-depth analysis of each
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7 project. Many of the projects involved relatively short-run repetitive manufacturing tasks. For
8
9 these projects, the learning curves associated with the repetitive manufacturing tasks were the
10
11 focus of a substantial part of the analysis carried out by the team. The team's focus was on
12
13 the impact of disruptions that occurred during the life of the project on the gains that had
14
15 been expected from any learning curve. To gain an understanding of the impact of the
16
17 disruptions, the team discovered the need to disaggregate a learning curve. During most
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19 repetitive manufacturing project, managers do not have the resources to have such in-depth
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21 analysis carried out. Therefore, in an attempt to help managers think through the impact of a
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23 disruption on their own projects, this paper aims to provide managers with an understanding
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25 of the disaggregation process of a learning curve.
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3. Learning in disrupted projects

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38 When a project is disrupted, project managers need to be able to forecast the impact of the
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40 disruption on the project, including any 'lost learning' so that they can assess the impact on
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42 the project and seek to manage the situation better. If a customer triggered the disruption,
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44 then this may also be beneficial in order to claim compensation for the disruption in either
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46 additional time or cost (Ackermann et al. (1997); Williams et al. (2003)).
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53 When assessing the impact of the disruption on the project, understanding the impact on
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55 learning is important to enable decisions to be made on actions that need to be taken in
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57 response to this disruption. Various authors have explored the impact of disruptions, such as a
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59 break in production, on learning through forgetting and re-learning. Examples of such work
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3 are Globerson et al. (1989), Shtub et al. (1993), Badiru (1994), Arzi and Shtub (1997), Ash
4 and Smith-Daniels (2004) and Norfleet (2004). These studies look at the overall cost to
5 labour, but do not explore the impact in sufficient detail to enable decisions to be made on
6 actions that need to be taken in response to this disruption. For example:
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15 The disruption may result in labour “going back up the learning curve” - meaning
16 there is a need to regain this learning. In these circumstances, managers need to
17 revisit the nature and extent of investment in new corporate learning.
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24 Effective management of the project demands knowing the impact of new labour on
25 any expected learning gains. Among other needs this will help management make a
26 decision between, for example, hiring new workers rather than using overtime or shift
27 working.
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36 In addition, it is important to know the learning expected after the disruption in order
37 to produce realistic performance indicators for the project.
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43 Graph 1: An example of disrupted learning (at unit 105) ABOUT HERE
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48 Graph 1 shows real data from aircraft manufacture. Here the complete labour force was
49 changed after the 105th unit as they were moved to another more urgent project. The graph
50 demonstrates that there was some impact of retained corporate learning, but that, for the most
51 part personal learning was lost.
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3 Although it is widely recognised that disruptions such as design changes and production
4 interruptions will affect learning on a project (for example Hall (1957); Garg and Milliman
5 (1961); Allemang (1977); Smunt (1986); Eden et al. (1998)), the common learning models
6 that are covered in the literature do not enable a manager to assess the impact of the type of
7 disruptions that are discussed above.
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17 Overall learning on a project is made up of many different components. For example,
18 Jefferson (1981) states that Northrop identified learning to arise from improvements to
19 tooling, quality control, design changes, manufacturing cost improvements, manufacturing
20 control and operator learning. Disaggregating each of these from the overall learning curve
21 assumptions, to enable a truly accurate assessment of the impact of a disruption on learning,
22 would not only be complex, but also controversial as there is no overall agreement on all the
23 different components that make up learning (Argote (1993)). Indeed some have referred to
24 this task as impossible (Dar-El (2000)). However, as a first step, there is general agreement
25 that at a macroscopic level, learning in an organisation is made up of two dominant elements;
26 personal/operator learning and corporate/organizational learning (Harvey (1979); Yelle
27 (1979); Reis (1991) - a short definition of PL and CL is not included at this stage since a true
28 understanding of how PL and CL are to be considered in this work requires a full description,
29 section 5 will cover this). If it is the case that a disruption does not impact these two elements
30 equally, then disaggregation of these two elements, at least, is required – providing there are
31 significant management benefits.
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55 In projects where learning on a repetitive task is expected, a learning curve is normally used
56 to represent the expected learning gains over the life of the project. It is the disaggregation of
57 this curve that will be considered here. The use of this curve will be discussed before
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3 considering its disaggregation into the two dominant elements of personal learning and
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5 corporate learning.
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10 This paper therefore reports on how personal learning and corporate learning might be
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12 usefully disaggregated.
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15 16 17 18 19 20 **4. The learning curve** 21

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24 The use of the learning curve to inform estimates of overall manufacturing times and create
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26 production targets is well established. Indeed research into developing better learning
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28 models continues (Zangwill and Kantor (1998); Zangwill and Kantor (2000)). The transfer,
29
30 and use, of learning curve technology from manufacturing to other arenas is also regarded as
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32 important, for example into food service operations (Reis (1991)), in pizza production (Darr
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34 et al. (1995)), and musical instrument and apparel manufacture (Baloff (1971)).
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41 The learning curve formulation remains at a high level, where the debate is about the nature
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43 of the learning curve formulation rather than the components that make up learning. The
44
45 gross predictive validity of different formulations has been explored through empirical
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47 studies (Alchian (1963); Hackett (1983); Teplitz (1991); Bailey and McIntyre (1997)), but the
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49 components of learning over time have not been subjected to the same exploration. Many
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51 authors have argued for the need to disaggregate the learning curve on the grounds that the
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53 dynamics underlying the learning curve are poorly understood (Dutton and Thomas (1984);
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55 Lieberman (1984); Argote (1993); Yelle (1979)). Mishina (1987)) argued that "...the
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57 concept of the learning curve has been established as a strictly empirical phenomena". It has
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3 also been stated that "the rationale underpinning of the LC [learning curve] is obscure"
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5 (Zangwill and Kantor (1998)). Although the learning curve literature has accumulated a
6
7 significant amount of evidence, little has been done as to the explanation of the phenomena.
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9 However, little progress has been made although there are some exceptions such as Zangwill
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11 and Kantor (1998) where they consider the use of a "learning cycle" to propose a different
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13 theory of continuous improvement.
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21 **5. Personal and corporate learning**

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24 When making use of the learning curve it is presumed that progress derives from different
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26 types of learning (Hayes and Wheelwright (1984)). Argote (1993) provides one of the best
27
28 reviews of different aspects of group and organizational learning - a review that includes
29
30 reference to the social psychology literature. Some authors have focussed on seeking learning
31
32 curves for individual workers (Uzumeri and Nemhard 1998; Nemhard and Uzumeri 2000).
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34 However, more generally in the literature, and what is relevant to the focus of this paper, is
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36 the understanding of two dominant categories of learning which are personal/operator
37
38 learning and corporate/organizational learning (Harvey (1979); Yelle (1979); Reis (1991)).
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40 There are different definitions of the boundary between these two types of learning. For the
41
42 purposes of this paper, we use a definition best suited for the analysis of disrupted projects.
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44 We distinguish between these two different types of learning in the following manner:
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53 *Personal* learning (PL) is that which would be lost if the individual worker was to be
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55 removed from a particular task. This would include both tacit knowledge (Polanyi
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57 (1962); Tsoukas (2003)) and knowledge that could be explicated, such as
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59 remembering instructions, procedures etc. Harvey (1979) argues that PL is made up
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3 of “increased dexterity in performing the motions of the task combined with a
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5 reduction of those motions to the minimum. The rate, and extent, of this learning may
6
7 be influenced by financial incentives.” This differs from our definition. For us, when
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9 the person leaves the task whatever knowledge they have goes with them. The
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11 learning is attributed to the person doing the task. The rate of PL is the rate at which
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13 an individual worker will learn how to do a task without any changes in processes or
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15 procedures (design or tooling). With repetitive tasks of assembly work (rather than
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17 machine-paced work) there is expected to be more scope for human learning (DeJong
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19 (1957)).
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25 *Corporate learning (CL)* is that part of overall learning that remains intact after an
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27 individual worker has been removed from the task. Distinguishing between PL and
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29 CL learning is problematic, and so defining corporate learning as that learning
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31 remaining after personal learning ensures completeness. There is some similarity
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33 between PL and CL and what Dutton and Thomas (1984) call autonomous and
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35 induced learning – where autonomous learning occurs automatically on-the-job.
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37 Nevertheless, corporate learning belongs to the organization, in the sense that it has
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39 been institutionalised or recorded in some manner that should enable a new worker to
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41 gain fully from the learning. This is often referred to as *organisational learning*
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43 (Yelle (1979); Teplitz (1991)). Harvey (1979) describes this as consisting “essentially
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45 of improving the definition of the task and creating the environment in which the task
46
47 can be performed effectively without interruption”. Hayes and Wheelwright (1984)
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49 state that this is a function of individual learning, selection & training, methods,
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51 equipment and technology, division of labour, product design, substituting materials
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53 and/or capital for labour, incentives & leadership. Hirschmann (1964) gives examples
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55 of CL (described as group performance in his paper) as new jigs or fixtures, different
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3 combinations of operating conditions to improve yields or new instruments to
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5 improve control. Other examples of CL are the introduction of tooling, clearer
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7 instructions, and improvements in methods by incremental design modification.
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12 It is unlikely that a disruption impacts PL and CL equally. Some disruptions may affect PL
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14 but not CL. For example, if a project experiences a particularly high turnover of staff, then
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16 this will have implications for the PL achieved on the project, but may have no impact on the
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18 CL that was expected to be gained. However, it is unlikely that only CL would be impacted.
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20 All disruptions to CL will also impact PL. This is because if a procedure is changed, then
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22 labour need to relearn that procedure and so PL is also impacted. Both PL and CL may be
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24 impacted, but in unequal proportions. For example, 50% of the design of a product may be
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26 changed during the project, and this results in staff needing to relearn 50% of the task,
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28 therefore 50% of PL is impacted. However, the new design may be something that the
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30 company has done before and so, say, only 25% of the design is actually new to the company
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32 and so they already have instructions in place to deal with the other 25% of the work. This
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34 means that only 25% of CL is impacted.
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44 Given that there are different impacts of a disruption on PL and CL, then this paper argues
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46 that at least the disaggregation of these two types of learning will be required if the impact of
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48 the disruption is to be understood and managed.
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51 52 53 **6. Disaggregating the learning curve** 54 55

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57 In real-world manufacturing, the estimation of the overall hours to complete a given number
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59 of products is generally based upon three factors:
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- i. The form of learning curve model that is to be adopted.
- ii. An estimate of the expected time a specific task will take after a given number of items.
- iii. An estimated overall Learning Curve Index (LCI). This will determine the rate of learning or slope of the learning curve that is being adopted. An LCI lies between zero and unity and is the factor by which the time taken for a unit is multiplied in order to determine the time taken for the unit that is twice the quantity (e.g. the time taken for unit 8 can be determined by multiplying the time taken for unit 4 by the LCI) (Wright, 1936; Teplitz 1991).

Here we will consider each of these elements in terms of the overall learning curve and also the types of assumptions that can be drawn from previous research when attempting to disaggregate learning between PL and CL.

5.1 The learning curve model

The most common type of learning curve model used is the log-linear model (Teplitz (1991)). This learning curve is given by the equation $y=T_1n^b$ where T_1 is the cost of the first unit of production, n is the amount of cumulative production and b is the slope of the line on a log-log graph. In manufacturing, the rate of learning is generally taken to be log to the base 2 – this presumption has remained since Wright's early paper (Wright (1936)).

When attempting to disaggregate the learning curve into PL and CL, an initial consideration is whether either of these separate elements follows a model similar to the overall learning curve. As workers on the job continuously learn from one unit to the next, PL is obviously continuous and so a smooth log curve is plausible. However, CL is more likely to consist of

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3 many discrete gains. Therefore, CL can only be a log curve when there are so many
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5 increments that they merge into continuous corporate learning gains and so appear relatively
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7 smooth.
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12 If it were assumed that PL and CL both followed log curves, then it could be suggested that
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14 the overall learning curve would then be a summation of the two curves. There is a similar
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16 procedure suggested when summing the learning from different departments in an
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18 organisation (Teplitz (1991) p54; Kantor and Zangwill (1991)). However, the aggregation of
19
20 two log curves does not produce an overall log curve, unless the two curves have exactly the
21
22 same slope. Nevertheless, if a log curve is not tested it becomes difficult to establish what
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24 type of curve is appropriate, unless CL is simply presumed to be the result of extracting PL
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26 from the overall curve. If the LCI's for PL and CL are reasonably close (with some
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28 discrepancy between the sum of the two curves as compared with the aggregated curve), then
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30 we may be prepared to accept the analysis as providing a better insight as to the impact of the
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32 disruptions than working with an aggregated curve. Delionback (1975) suggested a
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34 procedure for finding an approximate log curve for the overall learning curve, however he
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36 reports that this procedure leads to errors in the overall learning curve.
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46 Alternatively, if it is the case that the LCI's are significantly different then the following
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48 approach may be more acceptable. If it is presumed that PL can be represented as a smooth
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50 log curve (as there is empirical evidence that the overall learning curve fits a log to base 2
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52 curve), it is more likely that CL is the difference between the overall log curve and the PL log
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54 curve.
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3 In this paper we explore both of these approaches: i) assuming PL and CL both work to a log
4 curve; ii) disaggregating by extracting PL and assuming interaction between PL and CL.
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10 It should be noted that the log-linear curves discussed in the remainder of the paper have been
11 transformed into their power function equivalents for presentational purposes.
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15 16 17 5.2 Estimating the presumed labour hours for the nth unit

18 Ideally, if the labour hours taken for the first unit are known, then this can be used as the
19 starting point for projecting the learning curve and the LCI can be used to determine the
20 expected labour hours for all other units. This approach can be immensely unreliable because
21 the time taken for the 1st unit (T1) is unreliable. The nature of the curve tends to stabilise
22 later in production. Graph 1 demonstrates this problem.
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34 If the estimation is being made prior to the manufacturing of the 1st unit, then alternative
35 methods are necessary, and often more reliable. Instead, the time taken for the nth unit (Tn)
36 may be predictable with reasonable accuracy, through the use of historical records of times
37 for individual tasks or packages of tasks. Estimators often use the time taken to complete a
38 so-called “standard” task, based upon the historical data, taken from a record of the time
39 taken to complete similar tasks after, for example, 100 products. As shorthand, this is often
40 noted as the T100 time. By working backwards up the learning curve, the supposed labour
41 hours required for the 1st unit (T1) can be determined.
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55 5.3 Estimating the learning curve index

56 The estimate of the Learning Curve Index (LCI) is typically based upon specific knowledge
57 of the nature of the contract within the context of industry expectations. Thus, for example,
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3 an index of 0.80-0.85 is typical for the airframe or aerospace industry (Teplitz (1991), p48).
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5 Our own experience in aerospace and trainset manufacture reinforces the expectation and
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7 historical analysis of a LCI of 0.78 to 0.85. It is also interesting to note that in 1957 (DeJong
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9 (1957), p52) argued that a value of 0.80 is “considered more or less normal”.

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15 Other published research suggests the following:

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20 When considering learning rates for different departments, Delionback (1975)
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22 suggests that labour learning follows a 0.85 learning curve rate.
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27 In the context of tasks involved in the assembly of a major component of a transport
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29 aircraft, Harvey (1979) p52) states “a learning curve of 84 percent [0.84] would be
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31 obtained if there were no operator learning and 75 percent [0.75] if the same operators
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33 were able to stay on their tasks without interruption” (based on a normal LCI of 0.78).
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38 Jefferson (May 1981)), reporting on Northrop’s data, states that for a 75% learning
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40 curve over a set of 1000 aircraft, 22% of the learning is achieved as a result of
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42 learning by the operator. Also, Harvey, over 100 items and with a 78% overall LCI,
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44 indicates approximately 24% of learning gain is through PL (p55).
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51 The above has explored the types of assumptions that can be drawn from the other published
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53 research regarding the learning curve model, the learning curve index, and the labour hours
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55 for the nth unit. These assertions are relevant to resolving the issue of disaggregation. It is
56
57 our experience that those who estimate, at the beginning of a project, the overall hours
58
59 expected to carry out the whole of a manufacturing project can be reasonably accurate
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3 (excluding any disruptions that may occur on the project). This overall accuracy does not
4
5 extend to accuracy in prediction of T1 or indeed T100. Therefore, based on this assertion, the
6
7 overall hours for a disaggregated learning curve that uses, perhaps, different assumptions
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9 about the learning process still needs to equate to the total time the estimators expect it will
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11 take to manufacture the total number of units.
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18 **7. Exploring a disaggregated learning curve**

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22 The aim of this paper is to consider the usefulness of disaggregating PL and CL on the
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24 management of disruptions. The most significant managerial implication is that of enhancing
25
26 the ability to forecast labour requirements. When labour forecasts are low then the project
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28 becomes delayed, compression occurs, typically accelerating actions are taken and further
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30 disruption occurs. When forecasts are high then the extra labour is absorbed and lower
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32 productivity than possible arises.
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39 This section of the paper considers this aim by exploring the consequences of an example
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41 disruption from the perspective of the assertions made above: i) the use of an aggregated
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43 'basic' learning curve, ii) the basic learning curve split between personal learning and
44
45 corporate learning, iii) the use of a non-zero asymptote (incompressibility), and iv) the impact
46
47 of accounting for an interaction between corporate and personal learning. Each of these
48
49 approaches will be explored using each of the Jefferson (May 1981) and Harvey (1979)
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51 assertions. In doing so it will be important to recall that Harvey considers 100 units and
52
53 Jefferson considers 1000 units.
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3 For illustration only, we consider the following disruption: after the 10th item is produced a
4 change in design occurs and that 50% of the design has changed. Thus, the example
5 considers a disruption early in the project when the learning rate is high. If the disruption
6 were later then the impact of the disruption would be higher. For replication purposes, the
7 impact of the disruption has been calculated as follows: at unit 11, 50% of the design is
8 changed and so this portion of the task is assumed to take the number of hours it took to
9 complete 50% of unit 1. From this point on these hours follow a learning curve where unit 12
10 becomes unit 2, unit 13 becomes unit 3 etc.
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27 6.1 The aggregated 'basic' learning curve disrupted

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29 Graph 2 is based on a learning curve over 1000 products, where T1 is 1000 hours. For the
30 purposes of ease of display, in order to illustrate the impact of the disruption, an extract of the
31 curve is shown, with only the first 100 items. The solid line shows the LC if there are no
32 disruptions that impact learning on the project. If 50% of the task is new then this proportion
33 of the task will go back up the LC and so the dotted line represents the LC after the disruption
34 has taken place.
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57 In these circumstances, and based on Jefferson assertions with respect to 1000 units, the cost
58 of the disruption is a 8.44% increase in total hours over the first 100 items. Based on
59 Harvey's assertions with respect to 100 items, and using the same approach, the cost would
60 be 7.01%.

Graph 2: 75% LCI over 1000 items (following Jefferson) before and after a disruption

ABOUT HERE

6.2 The basic learning curve split between PL and CL

Here the basic LC is split between PL and CL, according to the following assertions:

- a) It was suggested above that it might be reasonable to assume that PL is a log curve, but that CL may or may not be. For this first case, assume that PL and CL are both log curves.
- b) Assume that all tasks (hours) can benefit from both PL and CL.
- c) Jefferson asserted that for a learning curve with a 0.75 LCI, over of 1000 aircraft, the operator achieves 22% of the learning as a result of personal learning. Assuming that the PL curve is a log curve and that all hours can benefit from PL, then this indicates a personal learning curve index (PLCI) of 97.7%¹. Similarly, Harvey's assertions indicate a PLCI of 96.8%². These will be used in the illustration.

To find a corporate learning curve index (CLCI), we meet the constraint of matching overall hours for 1000 items for Jefferson and 100 items for Harvey. For Jefferson the total expected hours for 100 items is greater by 41%, because there is more learning early in the run for the overall (non-disaggregated) curve. In our comparisons we are considering the impact over 100 items. For Harvey the total hours match precisely over 100 items, even though there is also more learning early in the run for the overall (non-disaggregated) curve, because this is the basis for his assertions. The implications of both Harvey and Jefferson are considered in our exploration of the impact of disruptions.

If these disaggregated outcomes are compared with basic overall curves derived from a 75% LCI for Jefferson and 78% LCI for Harvey then there is a difference in the curves.

Graph 3 shows, for example, the difference between the two curves for Harvey.

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3 Although the two curves are obviously not the same for Harvey (or Jefferson), we must
4
5 continue to use them to compare the impact of the design change considered above. Note that
6
7 when considering the first 100 items, the cost of disruption for Jefferson will be less than for
8
9 Harvey because both PLCI and CLCI are higher for Jefferson.
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15 Graph 3: ABOUT HERE
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20 Graph 4 and 5 demonstrate the impact of the design change on each of these curves. For ease
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22 of display, only the first 30 products are shown on these graphs.
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27 Graph 4: ABOUT HERE
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30 Graph 5: ABOUT HERE
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34 The main observation from both Graphs 3 and 4 is unsurprising. The additional hours
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36 expected from the impact of the design change (that is, the area between the solid and dashed
37
38 lines) is less when PL and CL are split. This arises because, in this case, although 50% of the
39
40 task is changed, it is assumed that the company has undertaken work in the past where 50%
41
42 of the new task has been done before and so they do not lose this learning. Therefore, the
43
44 impact on the CL gains is less than the impact on the PL gains. The ability to measure this is
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46 only possible if CL and PL are disaggregated. It is only when attempting to disaggregate that
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48 the question as to how much of the new tasks have been undertaken by the organization
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50 before becomes relevant and necessary.
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The cost of the disruption in each case is as follows. The absolute numbers are unimportant; rather it is that the expected labour demands are lower in each case when disaggregation is undertaken.

<i>Cost of disruption over 100 products when splitting PL & CL</i>	Jefferson	Harvey
Basic LC	8.44%	7.01%
Disaggregated LC	4.01%	5.30%
Proportional difference	0.48	0.76

Note that if Jefferson's assertions were taken over 100 products (rather than 1000 items) there would be a lower CLCI and the disaggregated LC would be 6.48% (rather than 4.01%) giving a proportional difference of 0.77 (equal to that for Harvey).

6.3 Exploring the role of asymptotes

One of the assertions used in the above example is that all labour hours can benefit from both PL and CL. If we now assume that this is not the case, and that, instead, PL is possible on only a certain proportion of the task, then this means that there is likely to be a limit to the extent to which the time to undertake a task can be reduced. This leads on to consideration of an asymptote for PL gains. The role of such an asymptote will be discussed next.

When disaggregating the learning curve it seems plausible to consider the proportion of the time taken to complete a task that can benefit from either PL or CL. For example, a typical learning curve projection assumes that PL is possible on all of the hours involved in the 1st unit – that is the asymptote is zero. In addressing the implementation of the learning curve on

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3 personal learning it may be important to establish the extent of learning that can be attained -
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5 the position of the asymptote.
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10 The above sections have discussed the consideration of the learning rate and overall labour
11 hours when disaggregating a LC between PL and CL. This was done within the context of the
12 most common type of learning curve model - the log-linear model. A common amendment to
13 the log-linear model is to incorporate a plateauing effect (Conway and Schultz (1959); Baloff
14 (1966)) or a non-zero asymptote (DeJong (1957)).
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24 An indication of the proportion of the task where PL is possible is therefore relevant to the
25 disaggregation of the learning curve within the context of managing a disrupted project. This
26 is related to the so-called “plateauing effect”. A plateauing effect reflects the situation where
27 labour ceases to learn and is the equivalent of a non-zero asymptote. The most common
28 reason for plateauing - a non-zero asymptote - to be incorporated into a LC is because there
29 may be a limit to the minimum time taken to complete a task regardless of how many
30 repetitions are made. DeJong (1957)) describes this as incompressibility.
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43 When considering whether or not asymptotes do occur, Dar-El (2000)(2000, p19) notes that
44 there are “two references in the literature which state that learning continues even in the
45 millions, however, in practice when the number of cycles runs into the thousands
46 performance times tend to asymptote”.
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54 An asymptote is used in curves such as DeJong’s (DeJong (1957)) model, which adapts a log-
55 linear model by incorporating an incompressibility factor. This is an allowance that is made
56 because machine-time is not compressible as the number of units increases. Dar-El (2000,
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3 p70) argues that “any review of learning curve literature, would refer to DeJong’s model as
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5 ‘appealing’ – but in reality, it was *useless* – because of our inability to find an accurate value
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7 for M [the incompressibility factor]”. However, Cochrane (1968) quoted in Teplitz (1991),
8
9 supplies sample incompressibility factors. For example he suggests that the asymptote for a
10
11 machine shop operation occurs at 77% of the hours taken to produce unit 1 whereas for
12
13 aircraft subassembly the asymptote occurs at 43%.
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20 When considering the existence of an asymptote for PL or CL, De Jong (DeJong (1957))
21
22 states, “where no technical or organizational changes are made for a given task [that is
23
24 corporate learning], it appears – *as is only to be expected* – that [Tn] tends to approach a
25
26 certain limit value”(p53, our emphasis). This implies that it is likely that an asymptote exists
27
28 for PL. That is, the potential amount of PL to be gained is restricted by the given set of tasks
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30 that need to be performed.
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36 However, DeJong (DeJong (1957), p53) also states “in the ... case...when technical
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38 equipment and organization are gradually improved [that is, corporate learning is included] it
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40 does repeatedly happen that the fall in [Tn] is in accordance with [the normal LC formula -
41
42 with no asymptote] even over a relatively long period”. DeJong is therefore suggesting that
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44 an asymptote does not occur for the overall LC that includes both PL and CL. The reason for
45
46 this could be that CL can potentially remove or replace tasks, change the nature of tasks
47
48 through, for example, tooling, and reduce the size of the task to be completed. Thus, there is
49
50 no obvious non-zero asymptote for CL. The basic task that is to be performed could
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52 dramatically change throughout the project due to CL.
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60 Thus, we consider the following situation for an overall curve:

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3 If we take the situation of aircraft assembly, then Cochrane (1968) asserts that an
4 overall asymptote should occur at 43% of the hours of the first unit.
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8 We intend to split the curve between PL & CL and it has been argued that PL may
9 have an asymptote, but that CL does not.
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15 Based on Jefferson's assertions, we use an overall LCI of 75%. The basic LC is split between
16 PL and CL with the value of CLCI and PLCI being calculated in order to minimise the
17 variance between the basic LC and the split LC over 1000 products and the PL gain over
18 1000 products is approximately 22% of the overall learning gain. This results in a PLCI of
19 95.3% and a CLCI of 86.1%.
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29 For Harvey's assertions, the same procedure results in a PLCI of 93.6% and a CLCI of
30 85.7%. The difference between the basic LC and the disaggregated curve with an asymptote
31 is shown in graph 6 below.
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36 Graph 6: ABOUT HERE.
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41 As for the previous example, the two curves are not the same. However, as before, we use
42 them to compare the impact of the design change disruption. Graphs 7 and 8 demonstrate the
43 impact of the design change on each of these curves.
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51 Graph 7: ABOUT HERE
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53 Graph 8: ABOUT HERE
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57 As for the previous example, the main observation from Graphs 7 and 8 is that the additional
58 hours that are expected from the impact of the design change (that is, the area between the
59
60

solid and dotted lines) is less when PL and CL are split compared to the impact on the basic LC.

The cost of the disruption in each case is as follows:

<i>Cost of disruption over 100 products when splitting PL & CL with a non-zero asymptote</i>	Jefferson	Harvey
Basic LC	8.44%	7.01%
Disaggregated LC	4.06%	5.28%
Proportional difference	0.48	0.75

In the case of this particular example disruption, the cost of the disruption is similar to the previous example where asymptotes was not taken account of, and the shapes of the graphs are not significantly different.

6.4 Inter-relationship between corporate and personal learning

We have indicated above that gains in PL impact the extent of gains from CL, that is, introducing CL late in a project is likely to cost more in wasted PL than if introduced early. Thus, CL also impacts the gains in PL. For example, if PL can be shared and routinized across workers, then this will become CL. However, if the organisation makes improvements to its processes, then this will have an impact on individual workers learning. For example, if CL involves the introduction of new tools then individual workers will lose the learning that they have built up on the use of previous tools and so require to relearn the task. Also, if CL involves the introduction of new instructions on how to carry out a task, then this will affect the rate at which individual workers will learn. Therefore, PL must also be a function of CL.

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6 It was argued earlier that there is only a proportion of all of the tasks, or of each task, which
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8 is amenable to PL. However, in this case the amount of PL that can be obtained is a
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10 continuous function of the CL applied.
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15 For Jefferson, a 75% learning curve over 1000 sets reduces the time taken on unit 1 to 5.7%
16
17 of its value by the 1000th set. If it were assumed that a PL log curve could be produced and
18
19 that its initial value was taken as the total time taken on the 1st unit, then to meet Jefferson's
20
21 assertion, a PLCI of approximately 97.7% would be required. However, this assumes that
22
23 there is no interaction between CL and PL. When PL and CL are considered to be inter-
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25 related, a more complex approach is required.
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31 As CL and PL are inter-related the curve will be constructed iteratively. For example, the
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33 amount of PLG (Personal Learning *Gain*) and CLG for unit 1 will be required to be
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35 calculated, these will then feed into the calculations for PLG and CLG for unit 2 and so on.
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37 Thus, the labour-hours required to unit 3 (T3) will be equal to:
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$$40$$

$$41$$

$$42$$

$$43 T3 = T1 - PLG1 - CLG1 - PLG2 - CLG2$$

$$44$$

$$45$$

$$46$$

$$47$$

$$48 \text{ And } PLG2 = f(CLG1), CLG2 = f(PLG1)$$

$$49$$

$$50$$

$$51$$

$$52$$

53 Where, in general:

54
55 T1 = Labour-hours required to manufacture product 1

56
57 PLGi = Number of labour-hours learning gain between product i and product i+1 due to

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59 Personal Learning
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3 CLG_i = Number of labour-hours learning gain between product i and product i+1 due to
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5 Corporate Learning
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10 Not only are CL and PL a function of each other, but an organisation may choose not to
11 invest in CL because the extent of total PL gained over the production run does not warrant
12 the investment. This would be particularly relevant for projects where the number of items to
13 be manufactured is not large. Therefore, investment in CL is a judgment made by an
14 organisation dependant upon the extent of PL that has already been gained by workers. For
15 this reason it becomes important to be able to compute the extent of total PL gained before
16 the implementation of the proposed CL. Thus, disaggregation is important, not only when
17 considering disruptions but also when considering new proposals for achieving CL. When a
18 disruption occurs on a project, an iterative model can be used to help to assess the impact of a
19 disruption on the expected learning gains for a project. The expected learning gains for both
20 PL and CL, prior to the occurrence of any disruptions, can be determined using the above
21 procedure only.
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41 In order to illustrate the impact of an iterative model the following approach is taken:
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- 46 i. Begin with T₁: This may be known because unit 1 has already been completed,
47 otherwise it is calculated by going back up the overall learning curve from a
48 standard time at unit x.
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- 53 ii. Determine PL Curve: Assuming the asymptote is zero, then based on an estimate for
54 the PLCI, calculate PLG₁, PLG₂, PLG_i and so on. Based on Jefferson's assertions,
55 PLCI is 97.7% and for Harvey a PLCI of 96.8%.
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- iii. Calculate the CL gains between each product as the total gain between each product (based on the overall LC) minus the PL Gain between each product. This will result in a CL that is not a log curve.

Based on this approach, the impact of the design change considered in the previous example would be as shown in graphs 9 and 10 below.

Graph 9: ABOUT HERE

Graph 10: ABOUT HERE

The cost of the disruption in each case is as follows:

<i>Cost of disruption over 100 products when PL & CL Interact</i>	Jefferson	Harvey
Basic LC	8.44%	7.01%
Disaggregated LC	5.18%	4.58%
Proportional difference	0.61	0.65

8. Discussion

The table below shows a summary of the results from the example disruption when considered from each of the four approaches. It is unsurprising that in each of the disaggregated cases the impact of the disruption is less than when calculated using the basic learning curve model. Given the nature of this particular example disruption, the differences are such that, from the perspective of labour planning, disaggregation is likely to lead to the more efficient use of labour. Nevertheless, for reasons identified earlier, using Jefferson as

the basis for calculations might lead to too little labour being planned for and so possible further self-induced disruption from the need for accelerating actions. However, for the interactive model there is agreement.

Thus, it seems likely that disaggregation would be useful when considering disruptions of the sort discussed at the beginning of this paper. At the extremes, the role of disaggregation is obviously less significant: if all CL undertaken before the manufacturing commences (here there must be an expectation of no disruptions to the design of the product after production starts) then only PL can be gained during the project; if all of the tasks only involve machinery, then all CL and no PL to be gained during project.

The explorations above do suggest that it is feasible to use the sparse assertions from the literature (Jefferson and Harvey) to undertake a plausible quantitative evaluation. However, the consequences of using each of these assertions may, in many instances, provide very different forecasts of labour requirements, except when an interaction between PL and CL is considered.

SUMMARY	Jefferson	Harvey
Disruption of Basic LC	8.44%	7.01%
Cost of disruption over 100 products when splitting PL & CL	4.01%/ 0.48	5.30%/ 0.76
Cost of disruption over 100 products when splitting PL & CL with a non-zero asymptote	4.06%/ 0.48	5.28%/ 0.75
Cost of disruption over 100 products when PL & CL Interact	5.18%/ 0.61	4.48%/ 0.65

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6 The explorations undertaken have demonstrated that the disaggregation of a learning curve
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8 with respect to disruptions is a non-trivial task. The paper has highlighted a number of issues
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10 with current theories when considering the disaggregation of a LC.
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15 The 5 key elements of disaggregation are:

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17 (i) determining the boundary between PL and CL;
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19 (ii) determining whether either, or neither of PL and CL be represented as smooth log curves;
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21 (iii) establishing the typical learning rates for PL and CL and the proportion of overall
22
23 learning split between the two;
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25 (iv) establishing whether PL and/or CL learning reach an asymptote.
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27 (v) although it seems plausible that PL and CL interact, an interactive model has rarely been
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29 explored, and if it were used then how are PL and CL related.
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36 In this paper we have been considering the relatively short run of 100 items. However in long
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38 run cases there may be a need to account for the so called “dual-phase model” (Dar-El et al.
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40 (1995)). This seeks to account for the different rate of learning for cognitive task as compared
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42 to motor tasks, where cognitive learning is faster than motor learning. The LCI changes as the
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44 dominance of cognitive learning shifts to the dominance of motor learning.
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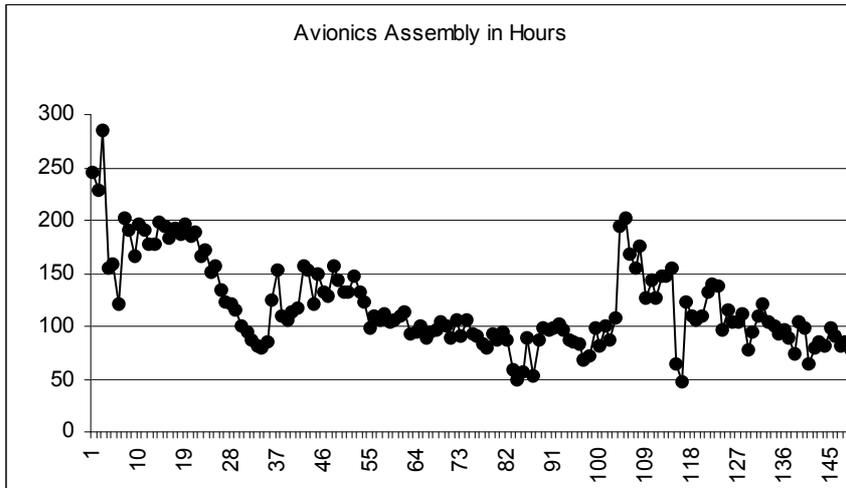
51 Through an exploration of the disaggregation process, a number of management insights have
52
53 been gained. An understanding of the process of disaggregation forces managers to ask
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55 important questions that may not be addressed otherwise.
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- 57
58 • The analysis draws attention to the differential impacts of personal and corporate
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60 learning under circumstances of disruption – managers are better able to consider

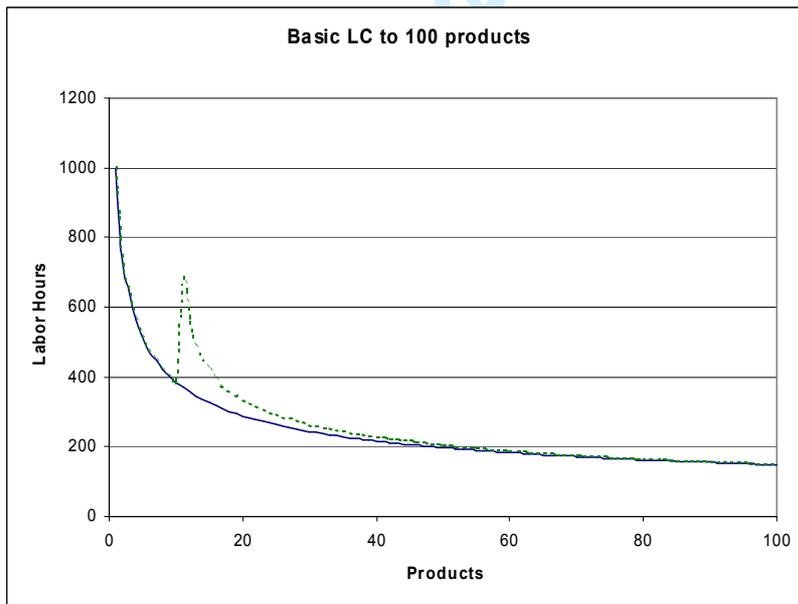
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3 appropriate mitigation actions. Similarly, it is only when seeking to disaggregate that
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5 the question as to how many of the new tasks that may be required following
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7 disruption have been undertaken by the organization before becomes relevant and
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9 necessary.
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12 • The process highlights that disaggregation is important, not only when considering
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14 disruptions but also, when considering proposals for gaining CL at the potential cost
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16 of wasted PL.
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20 • In addition, the requirement to make at least an assessment of the rate of personal
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22 learning may also have repercussions on non-disrupted learning estimates and so
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24 labour force targets.
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28 • The achievement of CL can change the nature of the tasks that are required to be
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30 performed and therefore suggest the requirement to consider the position of the PL
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32 asymptote, because the CL may change this.
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36 The test of the adequacy of any of the models derives from their ability to differentiate the
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38 consequences of different disruptions and so help in the ability to think through what to do as
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40 a manager, beyond any considerations for quantifying the real cost of learning losses from
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42 disruptions.
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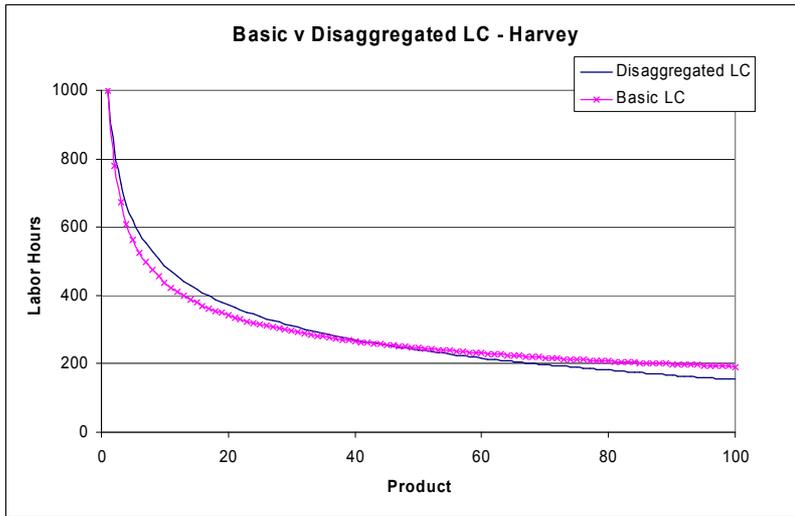


Graph 1: An example of disrupted learning (at unit 105)

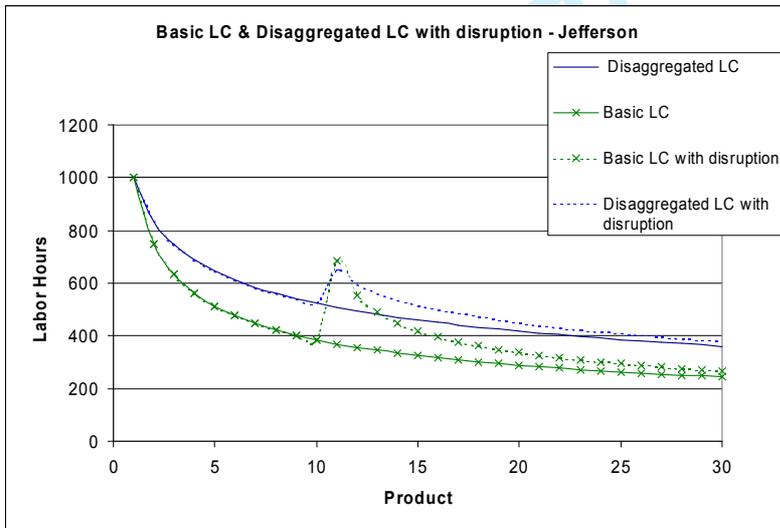


Graph 2: 75% LCI over 1000 items (following Jefferson) before and after a disruption

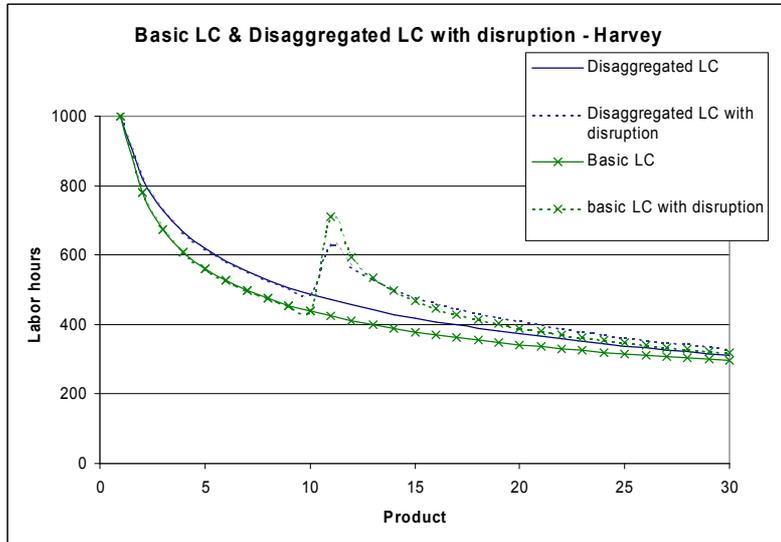
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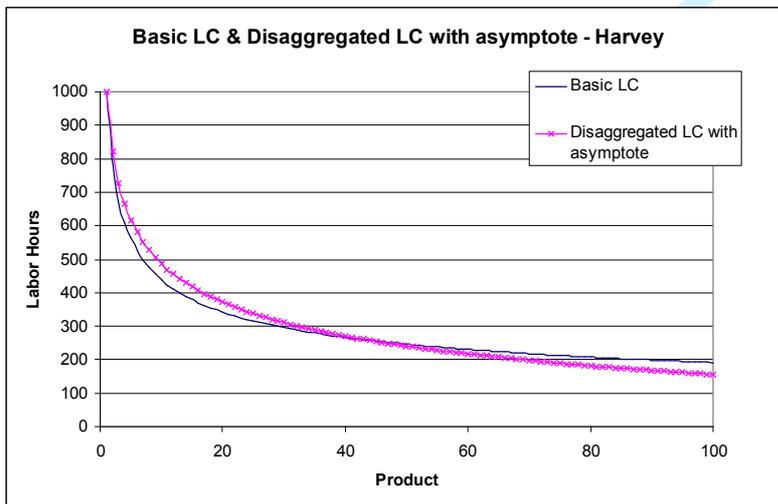
Graph 3: the difference between the basic LC curve (78%) and disaggregated curve for Harvey



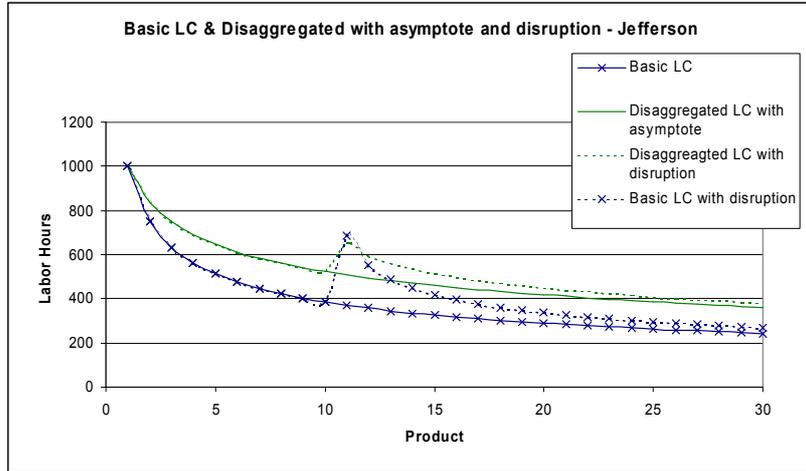
Graph 4: Impact of disruption on basic and disaggregated LC's for Jefferson's assertions



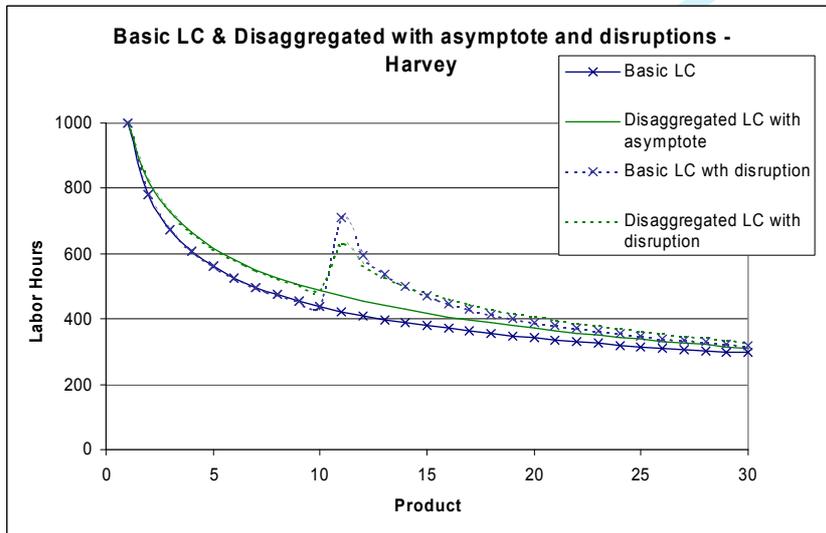
Graph 5: Impact of disruption on basic and disaggregated LC's for Harvey's assertions



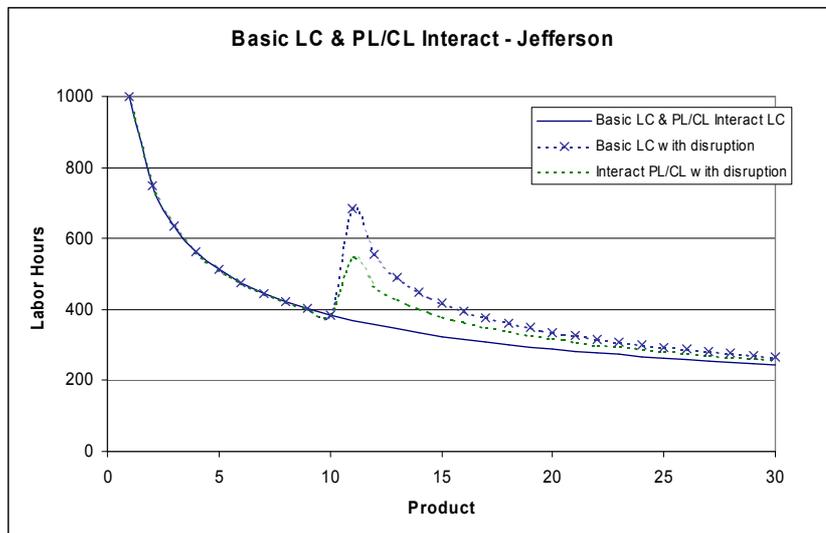
Graph 6: Comparison of basic LC and disaggregated LC with an asymptote based on Harvey's assertions.



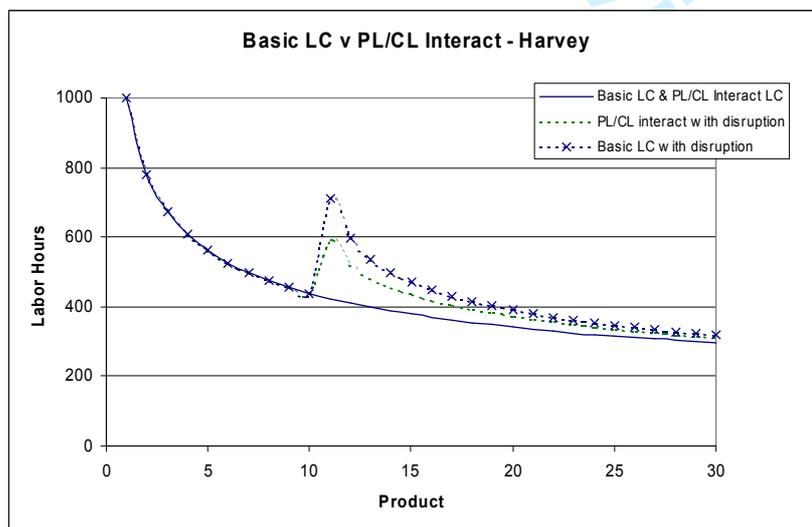
Graph 7: Impact of disruption on basic and disaggregated (with asymptote) LC's for Jefferson's assertions



Graph 8: Impact of disruption on basic and disaggregated (with asymptote) LC's for Harvey's assertions



Graph 9: Impact of disruption on basic and disaggregated (with interacting PL & CL) LC's for Jefferson's assertions



Graph 10: Impact of disruption on basic and disaggregated (with interacting PL & CL) LC's for Harvey's assertions

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Notes

1. Calculated by finding the PLCI that satisfies: $\{[T1-T1000]_{\text{where LCI=PLCI}}\} = 22\% \{[T1-T1000]_{\text{where LCI=75\%}}\}$

2. Calculated by finding the PLCI that satisfies: $\{[T1-T100]_{\text{where LCI=PLCI}}\} = 24\% \{[T1-T100]_{\text{where LCI=78\%}}\}$

For Peer Review Only

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