

Sensing endogenous seasonality in the case of a coffee supply chain

Abstract

Rogue seasonality, or endogenously generated cyclicity (in variables), is common in supply chains and known to adversely affect performance. This paper explores a technique for sensing rogue seasonality at a supply chain echelon level. A signature and index based on cluster profiles of variables, which are meant to sense echelon-level generation and intensity of rogue seasonality, respectively, are proposed. Their validity is then established on echelons of a downstream coffee supply chain for five stock keeping units (SKUs) with contrasting rogue seasonality generation behaviour. The appropriateness of spectra as the domain for representing variables, data for which is daily sampled, is highlighted. Time-batching cycles which could corrupt the sensing are observed in variables, and the need to therefore filter them out in advance is also highlighted. The knowledge gained about the echelon location, intensity and time of generation of rogue seasonality could enable timely deployment of specific mitigation actions.

Keywords: Supply chain risk, endogenous seasonality, bullwhip, sense and respond, clustering

1 Introduction

Supply chains are prone to disturbances, including those that arise endogenously from the use of inappropriate control systems and/or information to match supply with demand (Chopra and Sodhi, 2004). One such disturbance, characterised by endogenous generation of cyclicity in the profiles of system variables, is endogenous or rogue seasonality (Forrester 1961; McCullen and Towill 2002), a key but under-researched component of the bullwhip effect (Lee, Padmanabhan and Wang 1997; Fransoo and Wouters 2000; Holland and Sodhi 2004; Hussain and Saber 2012). Evident in several studies such as Kaipia, Korhonen, and Hartiala (2006) and Thornhill and Naim (2006), rogue seasonality tends to be misinterpreted as a cyclicity/seasonality in market demand and unnecessary managed (through ramping up and down of production and/or increase in stock levels) thereby increasing operating costs. The (adverse) cost implications are particularly severe for multi-echelon contexts where rogue seasonality could propagate to other echelons and cause a similar impact. Metters (1997) showed that costs to the extent of 10–20% could be reduced by the elimination of such seasonal variations.

One way of managing rogue seasonality, as suggested by Shukla, Naim, and Thornhill (2012) and Shukla and Naim (2015) and discussed in resilience terms by Purvis et al (2016), could be through ‘sense and respond’ (Haeckel 1999), where ‘sense’ means assessing a problem context through

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3 system information and appropriate models/filters/data-mining techniques, and 'respond', to the
4 subsequent initiation of suitable corrective action/s. Their suggested approach for sensing rogue
5 seasonality involves a signature and an index, where the signature is to indicate if rogue seasonality is
6 present/generated in a supply chain, and the index, to provide a measure of its intensity. Both the
7 signature and the index are defined on the basis of cluster profiles of variables such as order,
8 inventory and work in process that are represented as spectra, or amplitudes of sinusoids at various
9 frequencies, which was identified to be the most appropriate domain for representation. Different
10 supply chain contexts, both simulated and empirical, though only upstream ones were used for their
11 validation. However, these studies give rise to further questions such as:

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16 1) Instead of a supply chain level of sensing, is it possible to sense rogue seasonality at an individual
17 echelon (in a supply chain) level through an appropriately defined signature and index? Also, whether
18 such a sensing could be done over time in a monitoring mode? Rogue seasonality could then be more
19 precisely determined in terms of generation location, intensity and time of generation, thereby
20 enabling more specific and timely mitigative actions to be deployed.

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24 2) Whether the signature and index could work with downstream or distribution/production-
25 distribution supply chain contexts? These differ from the upstream contexts considered in previous
26 studies in the following ways: i) There are (additional) time-batching related cyclicalities in order
27 and dispatch variables (Cachon 1999; Potter and Disney 2006) that could corrupt the signature and
28 index's logic; ii) Their operative level is more disaggregated, both product and time-wise; data, such
29 as at an SKU level and daily sampled that is appropriate for such contexts tends to be noisy, and could
30 affect the development of cluster profiles (Keogh and Kasetty (2003), and thereby the logic/validity of
31 the signature and index.

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37 This study is aimed at addressing these questions. The downstream end of a multi-echelon coffee
38 supply chain is used for the investigations, with the dynamics of variables for five SKUs being
39 separately analysed. The multi-echelon structure enables the validity of the echelon-level signature
40 and index (that are defined) to be assessed at different echelons. Daily data is considered for the
41 variables, and which is chosen for a length of time that enables the assessments to be made at
42 multiple/different time intervals. While the primary contribution of this study is towards sensing of
43 rogue seasonality, it also contributes towards empirical rogue seasonality investigations and supply
44 chain dynamics assessments with low-level data, where there is a paucity of studies in the literature.

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50 The rest of the paper is structured as follows. Previous studies on rogue seasonality as well as its
51 sensing are discussed in the next section, while in Section 3, we explore the development of a
52 signature and an index for sensing it at an echelon (in a supply chain) level. Investigation of the coffee
53 supply chain from the perspective of rogue seasonality generation and its sensing is discussed in
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Section 4. In Section 5 the practical aspects of applying the signature and index are discussed with Section 6 being the concluding section.

2 Rogue seasonality and its sensing

2.1 About rogue seasonality

Rogue seasonality is a seasonal or cyclic pattern, of any time period, in orders and other supply chain variables that does not originate from consumer/exogenous demand but instead is created endogenously from the inventory and production control system structures used (Forrester 1961; McCullen and Towill 2002). Though commonly observed (Kaipia, Korhonen and Hartiala 2006; Torres and Moran 2006; Thornhill and Naim 2006) academic interest on rogue seasonality has been limited. Few studies have exclusively focussed on it with most considering it together with the Bullwhip effect, which involves amplification of orders from downstream to upstream echelons (Forrester 1961; Miragliotta 2006; McCullen and Towill 2002). This is true for the works of Dejonckheere et al (2003) and Jaksic and Rusjan (2008) as well; the focus there again is on the Bullwhip effect, but because the investigations are undertaken in the frequency domain, rogue endogenously generated cycles are indirectly analysed. The analyses though are analytical rather than empirical, and for one variable, namely orders rather than multiple ones typically associated with rogue seasonality; the range of cycles considered too are appropriate for Bullwhip rather than rogue seasonality investigation. Other more rogue seasonality focussed studies include those of Kim and Springer (2008, 2010) and Spiegler and Naim (2017). Their focus is on studying rogue seasonality generation characteristics and proposing design formulations such as optimum ordering policies to be used to minimise the strength of the generation. Analytical system dynamics approaches are used, which therefore meant tractable or simplifying assumptions such as dyadic structures and rationality in ordering having to be made. Though useful, policies developed under such simplistic assumptions may have limited relevance for real world contexts characterised by dynamic uncertainties, differing member objectives/constraints and behavioural biases in decision making. Top down design based approaches for rogue seasonality therefore need to be complemented with the bottoms-up sense/detect and respond based approach (Haeckel, 1999).

2.2 Rogue seasonality sensing approaches

Three studies, Thornhill and Naim (2006), Shukla, Naim, and Thornhill (2012) and Shukla and Naim (2015), have explored sensing of rogue seasonality, with 'sense and respond' (Haeckel 1999) as the underlying approach. While Thornhill and Naim's (2006) sensing technique has subjective elements, Shukla, Naim, and Thornhill's (2012) approach, that is based on a signature to assess presence/generation and an index to indicate the intensity of rogue seasonality in a supply chain is more objective, versatile and automation-friendly. The signature is defined as follows: *Rogue seasonality is considered generated/present in a supply chain when its system variables are clustered*

away from exogenous demand, and not otherwise, where clustering is used to record the similarity/dissimilarity relationships. The index is based on the logic of the signature, but with numerical values used to represent variable profiles and profile relationships. The specific logic is: a greater intensity of rogue seasonality in a supply chain would mean system variables across the supply chain being more tightly aligned to each other, causing their mutual dissimilarities (the denominator in the index) to be lower, while increasing their dissimilarities with exogenous or consumer demand (the numerator in the index), to ultimately cause the index to have a larger value. Two versions of the index, identified as index definition 1 and 2 are proposed, where the difference is in terms of whether the dissimilarity in the numerator is “minimum” or “average” as can be seen below. The rationale here is to assess if the logic of the index is robust to profiles of some system variables being different to the rest.

$$\begin{aligned} \text{Rogue Seasonality Index} \\ \text{for a supply chain} \\ \text{(Definition 1)} \end{aligned} = \frac{\text{Minimum dissimilarity between all system variables and exogenous demand}}{\text{Average dissimilarity between all system variables excluding exogenous demand}}$$

$$\begin{aligned} \text{Rogue Seasonality Index} \\ \text{for a supply chain} \\ \text{(Definition 2)} \end{aligned} = \frac{\text{Average dissimilarity between all system variables and exogenous demand}}{\text{Average dissimilarity between all system variables excluding exogenous demand}}$$

On testing, both the index definitions were found to be similarly effective. Spectra or amplitudes of sinusoids at different frequencies (after Fourier transform) was identified to be the most appropriate domain for representing variables when deriving the signature and the index. While Shukla, Naim, and Thornhill (2012) used different simulated contexts and an empirical steel context, Shukla and Naim (2015) established the signature’s and index’s validity with a more complex supply chain system that incorporated backlogs and quantity batching in ordering and shipping and considered more realistic ordering policies. While the index was seen to be valid as such, the signature required tweaking in the form of a threshold for proportion of variables that could be clustered with exogenous demand (and the context to still be classified as having rogue seasonality present/generated) needing to be specified.

2.3 Gaps in previous sensing approaches

While Shukla, Naim, and Thornhill’s (2012) signature and index propositions for sensing rogue seasonality are novel, they are defined for a supply chain as a whole; also, the rogue seasonality is assumed to be present in all or most variables across the supply chain except consumer or exogenous demand, termed the reference variable. Discrimination and identification of problematic supply chains, from a rogue seasonality perspective, is therefore possible. But what about individual echelons within supply chains? They are where rogue seasonality generation actually takes place, and where countermeasures need to be applied in practice. By sensing rogue seasonality at a supply chain

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3 echelon level and identifying those that are problematic, specific echelon level corrective actions
4 would be possible to further minimise the economic consequences of rogue seasonality.
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7 Such a level of sensing is appropriate from a technical perspective as well: in many supply chain
8 contexts all echelons may not show rogue seasonality that is assumed in the existing supply chain
9 level signature and index approaches. This could happen, for example, where a) the customer-facing
10 echelon and other echelons at that end operate on a make-to-order basis that is associated with no
11 rogue seasonality generation (Shukla, Naim, and Thornhill 2012); or where b) rogue seasonality is
12 generated in one of the middle echelons in a supply chain and while it may propagate upstream,
13 echelons downstream do not show it.
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17 Echelon level sensing of rogue seasonality is therefore relevant. However, the question that arises
18 then is whether we need a separate signature and index for that level; or the existing supply chain
19 level approaches could be applied given that an echelon is also technically a 'supply chain' in its own
20 right. Prima facie, the latter would work for the most downstream echelon but not for others. For the
21 most downstream echelon, "all system variables" in the definition would mean those for that echelon,
22 while the reference variable for sensing rogue seasonality would be exogenous demand; the supply
23 chain level signature and index can therefore be seen to apply for this echelon. For being able to sense
24 rogue seasonality at other echelons however, the reference variable would need to be not just
25 exogenous demand but also all echelon variables downstream of the echelon under consideration;
26 only then would it be possible to isolate the rogue seasonality generation characteristics for that
27 echelon. The signature and index definitions for sensing rogue seasonality at an individual echelon
28 level would therefore be different from those for the supply chain as a whole, and which need to be
29 developed and then validated.
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39 Another deficiency of the previous work is that the signature's and index's effectiveness is not
40 established for sensing rogue seasonality at different time intervals (in a monitoring mode); rather, the
41 related evaluations in Shukla, Naim, and Thornhill (2012) and Shukla and Naim (2015) are done at
42 one time with all available data. Success with the former could enable earlier detection of rogue
43 seasonality, and thereby in quicker initiation of corrective response/s to ultimately lower the economic
44 consequences of rogue seasonality.
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49 Finally, the signature and index in Shukla, Naim, and Thornhill (2012) and Shukla and Naim (2015)
50 are based on upstream supply chain contexts only; downstream or distribution/production-distribution
51 contexts, whose dynamic characteristics are more complex are not considered. Even Shukla and
52 Naim's (2015) work, which is based on the Beer game supply chain (Sterman 1989) that is technically
53 a production-distribution or downstream context, does not incorporate these complexities, which are:
54 a) Time-batching related cyclicity in ordering/despatch. This cyclicity is because of
55 transportation efficiency and ease of management considerations (Cachon 1999; Potter and Disney
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2006), and could differ across echelons in a supply chain due to differences in their cost structures and volume of goods handled (Burbidge 1994). For a production-distribution system, this difference could stretch upto the production echelon, with production batching cycles differing from those pertaining to dispatches to downstream echelons (Hejazi and Hilmola 2006; Taylor and Fearné 2009). Presence of these (additional) endogenously generated time-batching cycles could interfere with the signature and index's logic/validity.

b) Disaggregated nature of the operations, both product and time-wise. This is on account of downstream contexts' proximity to end customers (that have specific product demands) and their decision making requirements being more operational in nature respectively. The granular data, such as at an SKU level and which is daily sampled that is relevant to such contexts tends to be noisy and irregular; the cluster profiles for such a data may not conform to the logic of the signature and index (Keogh and Kasetty, 2003; Liao, 2005), and this needs to be assessed. Previous rogue seasonality sensing investigations have considered only monthly and product-wise (on a weight basis) aggregated data. In general also, few studies, including those on the bullwhip effect, have assessed supply chain dynamics with SKU level daily data. This, despite the rationale for doing so being supported by the literature (Fransoo and Wouters 2000; Chen and Lee 2012), and the availability of granular data (through RFID technology) and associated analytical techniques (de Kok et al. 2005; Lee and Ozalp 2007) increasing the practical relevance of such studies.

This study seeks to fill the above discussed gaps through investigations on a downstream coffee supply chain; the dynamics of variables (from a rogue seasonality sensing perspective) for five SKUs are analysed, both across echelons and over time, with daily data being used for the variables. However, echelon-level signature and index definitions need to be developed first.

3 Rogue seasonality signature and index for an echelon (in a supply chain) level

Given that supply chain-level signature and index definitions already exist, we explore if these could be adapted to work at an echelon level, and what, if any, changes are needed. In these (supply chain level) definitions, the supply chain as a whole is considered to be one entity with profiles of all the variables across the supply chain (i.e. covering all constituent echelons) together being therefore compared against market or exogenous demand's, which is considered as the reference variable. Applying this logic to an echelon level (of sensing) would mean that variables whose profiles are considered for comparison as well as the variables to whose profiles they are compared with, or the reference variable/s, would change with the echelon under assessment. For example, for sensing at the most downstream echelon, profiles of variables for that echelon would need to be compared against that for exogenous or market demand. For the next upstream echelon, it would mean comparing the profiles of variables for that echelon with those for all downstream echelon variables as well as exogenous or market demand. Generalising this pattern and using the existing (supply chain level)

signature definition as the basis, the signature for an echelon in a supply chain can be defined as follows: *Rogue seasonality is considered generated at an echelon when system variables for that echelon are clustered away from all downstream echelon variables and exogenous demand, and not otherwise.* The index to indicate the intensity of rogue seasonality generated at an echelon level can be similarly adapted from its supply-level version as follows:

$$\text{Rogue Seasonality Index for an echelon in a supply chain (Definition 1)} = \frac{\text{Minimum dissimilarity between system variables at that echelon and all downstream echelon variables incl. exogenous demand}}{\text{Average dissimilarity between all system variables at that echelon}}$$

$$\text{Rogue Seasonality Index for an echelon in a supply chain (Definition 2)} = \frac{\text{Average dissimilarity between system variables at that echelon and all downstream echelon variables incl. exogenous demand}}{\text{Average dissimilarity between all system variables at that echelon}}$$

These echelon-level index definitions are expected to work in the same way as the supply chain level ones discussed earlier in Section 2.2. Though logical, they need to be validated with a realistic context, as is discussed in the next section.

4 Coffee supply chain case study

The supply chain structure and flows as well as the nature of SKU's, system variables and data considered are explained/justified first. Profiles of the system variables are then used to support the assumptions made about downstream supply chain contexts as well as to investigate rogue seasonality generation characteristics. Finally, the signature and index are derived for individual SKU's at different echelons, and their validity is established. The signature and index are also derived at different time intervals to assess their (rogue seasonality) monitoring effectiveness.

4.1 Structure and flows

A downstream supply chain for coffee is considered for the investigations (see Figure 1 below), whose focal company, referred to as company M, is a part of a global food corporation.

Add Figure 1 here

Based on information gathered through interviews with company M's planning and distribution managers, the material flow across the supply chain is understood to take place as follows: Coffee is produced in batches at company M's factory and then transferred to two distribution centres (DCs), both company managed, with almost no stock held at the factory. Though company M actually has three factories, each product/SKU is produced in one specific factory only, and hence the representation of a single factory in the figure. From the DCs, the products/SKUs are shipped to company M's primary customers, which are large Retailers/Wholesalers, as well as to a Distributor

(referred to as WD) that services company M's small customers. Some inter-DC transfer of products/SKUs also takes place due to errors both in forecasting individual DC's requirements and in allocation. Supplies to WD are delivered to its nine depots, each uniquely assigned to the DCs, from where they are further supplied to the respective small customers. These depots are used by WD to service its own customers as well, given the (additional) Wholesaler role that it plays. As regards ordering by the small customers, they place their orders with company M, which then coordinates with WD for their servicing; in the case of a shortfall being anticipated at one of the depots, the required quantity of goods is dispatched there in advance. Inventory management at the DCs is done at an SKU level and is based on a periodic (weekly) review policy; in any week T, the status for week T+4 is assessed, and in the case of a shortfall being anticipated, a production request is initiated. This request is usually for a quantity which is greater of economic production quantity (EPQ) or one week's requirement for that SKU.

4.2 Nature of data considered

4.2.1 SKUs considered

With the focus being on investigations with disaggregated data, SKU-level data is considered. As will be seen later, this is an appropriate (product-wise) disaggregation level for the context under investigation here. A sample of five SKUs with varying sales volumes (in cases) and produced in different factories are considered, which are as follows: SKU1: 1% of total sales volume, produced in Factory 1; SKU2: 1% of total sales volume, produced in Factory 2; SKU3: 3% of total sales volume, produced in Factory 3; SKU4: 9% of total sales volume, produced in Factory 3; and SKU5: 1% of total sales volume, produced in Factory 3. Different sales volumes could mean different regularity in variable profiles that could make for a more robust assessment of the signature and index, as will be seen later.

4.2.2 Variables considered

Sensing, including of rogue seasonality, requires time series data on system variables. For the coffee supply chain, these variables (in units of cases), are 'A', 'B', 'C', 'D', 'E', 'F', 'G1 to G5', 'H1 to H4', 'I1 to I9' and 'J1 to J9', with their descriptions given in figure 1. No data was available on WD's sales to its own customers at the depots, and in order to ensure that this does not influence the findings significantly, only SKUs where these sales were estimated to be small were chosen. For the chosen SKUs 1, 2, 5, 4 and 3, only 2%, 9%, 15%, 35% and 37%, respectively, of the products going into WD depots make their way to WD's own customers. Transaction times between supply chain entities, as per inputs of company M's managers, being of the order of days, daily data on variables was considered. As will be seen later, this is an appropriate (time-wise) disaggregation level for the context being investigated here. Another issue was the length of data to be collected, which needed to be such that signature and index assessments could be done at multiple/different time intervals, but

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3 structural shifts in data, if any, are avoided. One year's worth of data was considered appropriate, and
4 therefore daily data for one year for the above variables for each of the five SKUs was used for the
5 rogue seasonality sensing investigations. This data was extracted from company M's and WD's IT
6 systems.
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9 10 **4.2.3 Profiles of the variables considered**

11 One of the justifications of this study is that downstream supply chain contexts show certain
12 distinguishing characteristics which could affect the validity of the signature and the index for such
13 contexts. Ascertaining if these characteristics, such as time-batching, operative dynamics being at a
14 disaggregated level which necessitates use of such a level of data, and this data being noisy and
15 irregular, are actually present in the downstream (coffee supply chain) context being investigated here
16 is therefore important. To do so, time series and spectra profiles (refer to Appendix I for its
17 description as well as for other terms covered later) of the variables are plotted; Excel[®] and Matlab[®]
18 are used for the computations and plots. Spectra or amplitude of sinusoids at different frequency
19 channels (derived through Fourier transformation) is considered, as it is known to be effective for data
20 with cyclical characteristics, and which was also observed in Shukla, Naim, and Thornhill (2012) and
21 in Shukla and Naim (2015). These profiles for one of the SKUs, SKU1, are presented in Figure 2
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34 The profiles are based on de-trended and normalised data. This enables time series profiles to be
35 compared at the same scale, while unnecessary features near the zero frequency channel that could
36 complicate assessments are avoided for spectra profiles. For the spectra plot in Figure 2, the
37 horizontal axis is a normalised frequency axis such that 1.0 represents the sampling frequency. This
38 means that for the daily data that is used here, a spectral peak on the frequency axis, at say 0.2/day,
39 would correspond to a cycle in the time series of a period of 1/0.2 or 5 days. The spectra plot is seen
40 to stop at 0.5/day on the frequency axis because of the Nyquist sampling theorem, which requires a
41 sinusoidal signal to be sampled at least twice per cycle (Chatfield 2004). The spectra are scaled to the
42 same maximum peak height to enable better visualisation of their characteristics. The following can
43 be observed from the plots in Figure 2:
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- 49 • The time series plots clearly highlight the irregular and discontinuous nature of the data.
50 However, apart from this, no other insights including on time-batching are gained from these plots.
- 51 • The spectra profiles, on the other hand (and as expected) are seen to be more effective: peaks,
52 representative of a structured repeating pattern, are evident in the spectra for many variables. For
53 example, for variables 'A' and 'B', spectral peaks are seen at a frequency of 0.15/day (~ 7 day cycle),
54 while for others, such as 'E', 'F', 'G1 to G5', 'H1 to H4' and 'J1 to J9', these are seen at some/all of
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3 the following frequencies: 0.15/day (~ 7 day cycle), 0.3/day (~ 3 day cycle) and 0.43/day (~ 2 day
4 cycle). These peaks are all essentially reflecting the time-batching cycles present. These cycles also
5 appear to be different for different echelons, as per variables for those echelons. For example, while
6 time-batching cycles of frequencies 0.15/day (~7 day cycle), 0.3/day (~3 day cycle) and 0.43/day (~2
7 day cycle) are seen in variables '*J1 to J9*' that correspond to the WD depot echelon, those of only
8 0.15/day (~7 day cycle) are seen in variables '*A*' and '*B*', corresponding to the factory echelon. These
9 time-batching cycles, though of endogenous origin, appear to have a rational basis: for example, those
10 in variables '*J1 to J9*' appear to be on account of customers with different purchase volumes and who
11 are locationally dispersed being serviced at different frequencies to ensure cost effectiveness, while
12 that in variables '*A*' and '*B*' seems to be due to the weekly nature of the planning. The (order of days)
13 cyclical nature seen in variables also supports the choice of daily data for the investigations, which would
14 have been masked if weekly/monthly data was used. Finally, features at low frequencies of between
15 0.03/day and 0.005/day (~ 30 day to 200 day cycles) are seen in the spectra for variables '*A*', '*B*', '*C*',
16 '*D*' and the majority of the '*G*', '*H*' and '*T*' variables, which could be due to the end of
17 month/Easter/Christmas and other such factors.
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27 While the above discussion concerned SKU1, time series and spectra profiles of a similar nature were
28 observed for the other SKUs as well, though these are not included here due to a paucity of space. The
29 downstream coffee supply chain context here therefore shows the characteristics expected of a generic
30 downstream context except for (product-wise) disaggregated data, such as the SKU level being an
31 appropriate level; this will be done in the next section. We now focus on utilising the variable profiles
32 to investigate echelon-level sensing of rogue seasonality. The preference will be for spectra profiles
33 that were seen to be effective in uncovering cyclical features in the data. Though this effectiveness
34 was demonstrated by Shukla, Naim, and Thornhill (2012) and Shukla and Naim (2015), these
35 researchers utilised continuous data as opposed to the irregular and discontinuous kind seen here.
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4.3 Rogue seasonality investigation

4.3.1 Aggregation of entities and variables

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45 The downstream coffee supply chain under investigation has both a vertical and a horizontal structure
46 (refer to Figure 1): while Factory, Distribution Centre (DC), Large Retailers/Wholesalers/WD and end
47 customers are a part of the former, parallel entities at these stages, such as two DCs, nine WD depots
48 and two sets of end customers, i.e. WD's own customers and company M's customers, constitute the
49 latter. As various studies have shown rogue seasonality to propagate upstream, our focus here is
50 essentially on the vertical structure; the horizontal structure could therefore be compressed to create a
51 simplified and potentially more insight-yielding structure. This would mean combining parallel
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3 entities at the relevant stages as long as those entities, as assessed by comparing the profiles of their
4 variables, are similar. This is to ensure integrity in the aggregation.
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7 Combining the parallel entities and associated variables (data) results in the creation of the following
8 aggregated variables: total despatches from factory to DCs represented by variable '*A plus B*'; total
9 stock at DCs represented by variable '*C plus D*'; total despatches from DCs to large
10 Retailers/Wholesalers represented by variable '*E plus F*'; total despatches from DCs to WD depots
11 represented by variable '*G plus H total*'; total stock at WD depots represented by variable '*I total*' and
12 total customer M orders serviced at WD depots represented by variable '*J total*'. Though information
13 on WD's sales to its own customers at the depots was unavailable, and which therefore could not be
14 added to '*J total*', its influence on the dynamics is nonetheless curtailed through choice of SKUs, as
15 discussed earlier. Also, '*E plus F*' and '*G plus H total*' are kept separate rather than being combined
16 together, as their magnitudes were noted to be significantly different, which was expected to cause
17 their dynamic characteristics to differ, as will be corroborated later. The de-trended and normalised
18 time series and spectra profiles of the aggregated variables for each of the five SKUs are given in
19 figure 3 below.
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31 It is important to assess if the aggregation done was valid, and therefore spectra profiles of both the
32 variables that are aggregated and of the resulting aggregated variable were all compared to each other.
33 The three were found to be similar in all cases. For example, in the case of SKU1, profiles for
34 variables '*A*' and '*B*' (refer to Figure 2, right-hand panel) and of the aggregated variable '*A plus B*'
35 (refer to Figure 3, bottom half, first panel) are all similar with a spectral peak at frequency 0.15/day (~
36 7 day cycle). Similarly, spectra profiles for each of the '*J1*' to '*J9*' variables and the aggregated
37 variable '*J total*' are also similar with spectral peaks at frequencies of 0.15/day (~7 day cycle),
38 0.3/day (~3 day cycle) and 0.43/day (~2 day cycle). The aggregated variables therefore represent the
39 dynamics accurately and will be used for the subsequent investigations. One final point about the
40 profiles for variables '*E plus F*' and '*G plus H total*' is that these are seen to be different for most
41 SKUs (refer to Figure 3, bottom half), thereby supporting the original decision of not combining them
42 together.
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51 **4.3.2 Rogue seasonality presentation**

52 We now try to understand the nature of rogue seasonality present/generated, and therefore, profiles of
53 the aggregated variables in Figure 3 are examined.
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3 The time series profiles (refer to Figure 3, top half), as with unaggregated variables earlier, do not
4 appear to be useful with no cyclic features identifiable. What is highlighted is that the data is irregular,
5 that this irregularity is significantly more in order and dispatch variables than in stocks variables and
6 that it varies across SKUs; this last point increases our confidence that the sensing assessments are
7 robust. No other patterns are evident except in the case of SKU 5, where periods when no supplies
8 were made from factory to DC'S (refer to variable "A plus B"), which caused a reduction in total
9 stocks at DC's (refer to variable "C plus D"), that in turn led to a reduction in despatches from DC's
10 to Large Retailers/Wholesalers (refer to variable "E plus F") and to WD depots (refer to variable "G
11 plus H total"), the last potentially affecting WD's ability to service M's customers from its depots
12 (refer to variable "J total") are seen.
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19 The spectra profiles, on the other hand (refer to Figure 3, bottom half), as with unaggregated variables
20 earlier, are seen to be more effective, with the following being evident: 1) time-batching cycles
21 (reflected in the form of spectral peaks), which are different in some/all variables for an SKU; and 2)
22 elevated spectra values at low frequencies of between 0.03/day and 0.005/day (~ 30 day to 200 day
23 cycles) for most variables. However, variables are also seen to show different time-batching cycles in
24 different SKUs. For example, variable '*J total*' shows cycles of 2, 3 and 7 days for SKUs 1, 3 and 4,
25 but only shows cycles of 7 and 3 and 7 days in the case of SKUs 2 and 5, respectively. While this can
26 be explained as being due to the nature of factors that cause time-batching and their inputs being
27 different, it also demonstrates the unique nature of each SKU's dynamics. The choice of such a
28 (product-wise) disaggregated level, i.e. the SKU level, for the investigation is therefore justified.
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35 We now use the spectra profiles further to assess rogue seasonality or endogenously generated
36 cyclicity in variables. It is useful to clarify that unlike in previous rogue seasonality studies, where
37 rogue seasonality was the only endogenously generated cyclicity present, here, another cyclicity of
38 the same kind (of time-batching), and which is perfectly legitimate, is also present. In such cases, the
39 different endogenously generated cyclicalities present require further discrimination, with only the
40 illegitimate one, appearing as an unexplained cyclicity, being classified as rogue seasonality. The
41 spectra profiles are examined again closely, but now from this perspective. No unexplained spectral
42 peaks are apparent in any variable in the case of SKUs 1 to 4, with only those pertaining to time-
43 batching and at low frequencies discussed earlier being seen. This is true for variables in the case of
44 SKU 5 as well except for variable '*A plus B*', where, in addition to the spectral peak at low
45 frequencies of between 0.03/day and 0.005/day (~ 30 day and 200-day cycles), and another time-
46 batching-related one at frequency 0.15/day (~14 day cycle), a (smaller) unexplained peak at frequency
47 0.07/day (~14 day cycle) is also evident. Interviews were conducted with company M's personnel to
48 clarify this unexplained cycle, as per whom manufacturing-related problems had caused production
49 stoppages at certain times during the year (corresponding to the data). This is also supported by the
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3 time series profile for the '*A plus B*' variable for SKU 5, where several nil values, suggestive of no
4 despatches being made from the factory, are evident. The non-production in certain periods appears to
5 have caused a change in the factory production schedule and consequently a change in the schedule of
6 despatches made from there to the DCs, or in the '*A plus B*' variable, to create the 14 day cycle
7 therein that can be classified as rogue seasonality. Manufacturing problems, such as equipment
8 breakdowns and other supply disruptions, are known to affect the dynamics of variables (Taylor 1999;
9 Paik and Bagchi 2007), but their causing rogue seasonality generation as seen here has not been
10 discussed before. The rogue seasonality here is seen in only a single echelon, the factory echelon (as
11 per the variable for this echelon, '*A plus B*'), rather than echelons across the supply chain. An echelon,
12 rather than a supply chain level of sensing, is therefore more relevant here, as was discussed earlier in
13 Section 2.2. This factory-generated rogue seasonality could be transmitted to echelons upstream and
14 cause economic consequences there. Timely sensing and subsequent speedy management of this
15 rogue seasonality is therefore essential.
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24 **4.3.3 Rogue seasonality sensing at an echelon level**

25 After understanding the nature of rogue seasonality generated/present, we now explore its sensing at
26 an echelon level. This would mean trying out the echelon-level signature and index propositions
27 discussed in Section 3 and assessing their effectiveness. The assessments can be made at each of the
28 two echelons in the (aggregated) coffee supply chain of factory and WD depots; DCs are not
29 considered as a separate echelon, as their operations are jointly managed with the factory's.
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34 **4.3.3.1 Sensing based on the signature**

35 Referring to the echelon-level signature definition (refer to Section 3), and applying it at the factory
36 and WD depots echelons (for the five SKUs) would mean the following: for the factory echelon, the
37 nature of the clustering of '*A plus B*' (the only variable for this echelon) vis-a-vis the rest of the
38 variables (the downstream variables in this case; refer to Figure 1) will need to be compared; for the
39 WD depots echelon, this comparison will need to be between the two variables for this echelon of '*G*
40 *plus H total*' and '*I Total*', vis-a-vis the lone downstream variable, '*J total*'. Exogenous demand in the
41 definition is not relevant here as respective proxies, '*E plus F*' and '*J total*', are used. For clustering,
42 representing variables as spectra, as in Figure 3, would not be enough; these spectra would need to be
43 pre-processed as well.
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51 Features at unrelated frequencies in the spectra could interfere with the logic and computation of the
52 signature and index. The aim of pre-processing here is therefore to filter these frequencies out in
53 advance. Some frequencies of this kind with elevated spectra values are seen in the low frequency
54 range (refer to Figure 3, bottom half), similar to that in Thornhill and Naim (2006) and Shukla, Naim,
55 and Thornhill (2012); if not filtered out, they would tend to mask the rogue seasonality present. Given
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3 that transaction times between supply chain entities is of the order of days and a similarly sampled
4 data is used, frequencies lower than 0.03/day (or cycles of time periods greater than a month) could be
5 considered as low and filtered out from the spectra of all the variables. Another set of frequencies that
6 need to be filtered out here in order to effectively uncover rogue seasonality are those pertaining to
7 time-batching. For a particular echelon under evaluation, time-batching related frequencies present in
8 each of the relevant variables would need to be filtered out from all of those variables. For example,
9 in the case of SKU 2, for the factory echelon where all six variables are relevant, the time-batching
10 related frequencies seen in these variables of 0.15/day (~7 day cycle), 0.3/day (~3 day cycle) and
11 0.43/day (~ 2 day cycle) (refer to Figure 3, bottom half, second panel) would need to be filtered out
12 from all six variables. On the other hand, for the evaluation of the WD depots echelon for the same
13 SKU, the time-batching related frequency of 0.15/day (~7 day cycle) seen in the relevant variables of
14 'G plus H total', 'I Total' and 'J total' would need to be filtered out from all (these) three variables.
15 From the spectra plots in Figure 3, it is clear that for all the SKUs except SKU2, the filtered out time-
16 batching related frequencies for factory and WD depots echelon evaluations would be the same. It is
17 important to point out that while identification of the time-batching related frequencies, including
18 those which need to be filtered out, is done visually here, for a new/unknown context, this would have
19 to be done on the basis of historical data/patterns. Spectra of variables are filtered for the factory and
20 WD depots echelon evaluations as above for each SKU. This is done by replacing the spectra values
21 at the relevant frequencies with zeros. Variables are then clustered using Ward's algorithm (and
22 XLSTAT[®] software), with Euclidean distance as the dissimilarity measure. These cluster profiles are
23 presented in Figure 4 below. To conserve space, cluster profiles pertaining to the evaluation of the
24 factory echelon are only presented, with those pertaining to WD depots echelon being interpreted
25 from the same.

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43 Evaluating the signature at the factory echelon, with unrelated/interfering frequencies being filtered
44 away from all the relevant variables during pre-processing, rogue seasonality, if generated at this
45 echelon, would cause '*A plus B*' to be dissimilar to others. Therefore, it would also be clustered
46 separately. Such a cluster profile can be expected for the factory echelon in the case of SKU 5, where
47 rogue seasonality generation was evident (refer to Section 4.3.2). However, for the other four SKUs
48 with no rogue seasonality generation at the factory echelon, there is no reason for the '*A plus B*'
49 variable to be clustered separately from the other variables. Examination of the cluster profiles in
50 Figure 4 shows this to be true in both cases: while '*A plus B*' is clustered separately from other
51 variables in the case of SKU 5, it is clustered with them for SKUs 1 to 4. The signature is therefore
52 seen to work in detecting generation/non-generation of rogue seasonality at the factory echelon.

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3 We now assess the effectiveness of the echelon-level signature for the WD depots echelon. As per the
4 discussion in Section 4.3.2, no rogue seasonality generation was apparent in either of the two
5 variables, '*G plus H total*' and '*I Total*', for this echelon for any SKU. Therefore, if the logic of the
6 signature were to hold and non-generation of rogue seasonality for this echelon correctly indicated,
7 variables '*G plus H total*' and '*I Total*' and the lone downstream variable '*J total*' would need to be
8 not clustered separately. On examining the cluster profiles, this appears to be only partially true: while
9 '*G plus H total*' and '*J total*' are seen to be not separately clustered, this is not the case for '*I Total*'
10 and '*J total*'. As discussed in Shukla and Naim (2015), specification of a threshold for proportion of
11 variables that do not cluster as expected but for which the signature is still valid therefore becomes
12 relevant.
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19 Given the visual nature of the signature, which makes it subjective and operationally difficult to apply
20 in contexts involving a large number of supply chains/SKUs, a quantified version of the signature in
21 the form of an index of rogue seasonality becomes relevant.
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25 **4.3.3.2 Sensing based on the index**

26 The echelon-level index definitions (definitions 1 and 2) and logic are discussed earlier in Section 3.
27 Though index values as per definitions 1 and 2 were seen to be strongly correlated for the supply
28 chain version of the index, this may not be true for the echelon-level index and needs to be assessed.
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33 We now seek to derive index values for the factory and WD depots echelons for each SKU. For the
34 WD depots echelon, no problems are anticipated: dissimilarity among the echelon's variables, i.e. '*G
35 plus H total*' and '*I Total*', can be calculated, as can the dissimilarity between them and the
36 downstream variable, '*J total*'. However, for the factory echelon with only one variable, '*A plus B*',
37 average dissimilarity among echelon variables, or the denominator in the index, cannot be calculated.
38 One option could be to use average dissimilarity among all (its) downstream echelon variables (which
39 means the rest of the variables in the present context) instead. However, this could result in
40 underestimation of the index value, especially for the case where that echelon, i.e. the factory echelon,
41 is generating rogue seasonality. This is because the average dissimilarity between the echelon's, i.e.
42 the factory echelon's, variables in such a situation would actually be lower (on account of the shared
43 rogue cyclicity) than the one between (its) downstream echelon variables that is assumed. However,
44 in the case of no rogue seasonality generation at that echelon, i.e. the factory echelon, echelon
45 variables and downstream echelon variables profiles may not significantly differ, and therefore use of
46 the latter may not bias the index values significantly. Unlike the denominator, computing the
47 numerator in this case, which involves dissimilarities between '*A plus B*' and the rest of the variables,
48 is relatively easy. Index values were computed as per above for the factory and WD depots echelons
49 for each SKU, and based on both index definitions. These are presented in Table 1 below. Pre-
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3 processed spectra were used for the computations, as in the case of the signature, with dissimilarities
4 between them measured in terms of the Euclidean distance.
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8 Add Table 1 here
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10 On examining the index values in Table 1 and correlating them with generation/non-generation of
11 rogue seasonality in different contexts, we find a good correspondence. Rogue seasonality, as
12 previously seen in Section 4.3.2, is only generated at the factory echelon in case of SKU 5, with all
13 other contexts, i.e. factory and WD depots echelons in the case of SKUs 1 to 4 and WD depots
14 echelon in the case of SKU 5, showing no rogue seasonality generation. The index values in Table 1
15 accurately reflect the same: index value for the factory echelon for SKU5 (shaded) is greater than that
16 for each of the other contexts, and for both index definitions. However, to incorporate rigour into the
17 assessment, the index value for the former is compared with the pooled/average index value for the
18 latter, which includes all the contexts with no rogue seasonality generation; the difference between the
19 two of 2 and 3.5 times standard deviation of index values for index definitions 1 and 2, respectively, is
20 significant. This (significant) difference is despite the index value for the former, i.e. for the context
21 with rogue seasonality generation, being an underestimation due to the nature of assumptions made in
22 computation, as discussed earlier. The index (both definitions) therefore appears to be effective in
23 discriminating echelons with different intensities of rogue seasonality generation, which for the
24 present case meant generation/non-generation of rogue seasonality. Correlation between index values
25 based on the two index definitions was observed to be high at 0.83, suggesting both to be similarly
26 representative of the index's logic. Either could therefore be used, though thresholds for classifying
27 whether an echelon is generating/not generating rogue seasonality would be different, and which
28 would need to be specified, for each case.
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39 **4.3.4 Rogue seasonality sensing over time**

40 After establishing the feasibility of sensing rogue seasonality at an echelon level, we now explore if
41 this sensing could be done across time. This would require investigations of the previous section that
42 were done in a one-time mode, i.e. at the end of a year using the previous 365 days' data, to be
43 repeated at different (shorter) time intervals. With shorter time intervals (or shorter time series),
44 frequency channels in the spectra representation would be fewer, and resolution of the spectral peaks
45 would therefore be poorer; the signature's and the index's effectiveness for sensing rogue seasonality
46 may, as a result, be compromised. This is even more relevant in the present context, where there are a
47 significant number of zero entries in variable data (refer to Figure 3, top half) due to the investigations
48 being at a disaggregated level. However, a shorter time series has its benefits, such as rogue
49 seasonality generation being sensed earlier. We consider an assessment done every 3 months, but
50 based on the previous 6 months' data, to be an appropriate compromise: while the former ensures
51 sensing of rogue seasonality to be reasonably timely, the latter ensures that there are enough data
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3 points for the signature and the index to be effective in sensing. The echelon-level signature's and
4 index's effectiveness were therefore assessed as follows: at the end of month 6 using the previous 6
5 months' data, at the end of month 9 using data from months 4 to 9 and at the end of month 12 using
6 data from months 7 to 12. All the steps followed earlier, i.e. representing variables as spectra, pre-
7 processing them, clustering them for the signature and computing index values for each of the factory
8 and WD depots echelons for each SKU, are now repeated for each of the above time intervals.

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13 We first examine the spectra profiles of variables at different time intervals. The spectra profiles for
14 SKU5, where rogue seasonality generation is evident (at the factory echelon), and for SKU2, where
15 this is not so, are plotted in Figure 5 below. Rogue seasonality index values for the factory echelon at
16 different time intervals for each case are also presented. These were computed using filtered spectra
17 as earlier.

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24 Examining the profile of variables for SKU5 (refer to Figure 5, top half panels), no significant
25 difference is seen in the profile of a variable across the three time intervals except in the case of
26 variable '*A plus B*'. For '*A plus B*', while the 14 day rogue seasonality seen earlier in its full-year
27 data-based profile is evident in its profiles based on data from months 1 to 6 and months 4 to 9 (refer
28 to the first two panels), this is not so for its profile based on months 7 to 12 (refer to the last panel).
29 From this, it can easily be deduced that the rogue seasonality generation (at the factory echelon) in
30 this case was happening between months 4 to 6, and perhaps between months 1 and 3 as well,
31 although the latter cannot be confirmed. A shorter time interval of sensing, i.e. quarterly instead of
32 yearly, has therefore enabled the rogue seasonality generation determination to be earlier, i.e. the end
33 of month 3 or 6 rather than end of the year. The echelon-level signature based on cluster profiles (not
34 presented here to conserve space) was also seen to accurately indicate generation of rogue seasonality
35 for the first two time intervals and non-generation for the last. The index's effectiveness is also
36 evident, with high index values being seen for the first two time intervals and a low value for the last.
37 In contrast to SKU5, for SKU2, no rogue seasonality generation (at the factory echelon) is apparent
38 for any of the three time intervals (refer to Figure 5, bottom half panels), as was the case with its full-
39 year data. This is also accurately reflected in the index values; index values for all three time intervals
40 for this SKU are much lower than that for the time interval corresponding to rogue seasonality
41 generation in the case of SKU5.

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The above discussion pertained to only the factory echelon and for only two SKUs. We now seek to
include the rest of the echelon contexts, i.e. WD depots echelon for all five SKUs and factory echelon
for SKUs 1, 3 and 4, in the assessment. None of these contexts showed rogue seasonality generation
as per the year-long data-based assessment discussed earlier. Index values for these as well as the

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3 earlier discussed contexts are provided in Table 2 below. These are computed from filtered spectra of
4 relevant variables as was discussed in Section 4.3.3.2 earlier.
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8 Add Table 2 here
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10 Examination of Table 2 reveals the following:

- 11 1) Index values for all three time intervals for the echelon contexts where no rogue seasonality
12 generation was apparent earlier are seen to be low (refer to the unshaded values in Table 2); the
13 average index value for these contexts across time intervals is 0.86 and 0.95 (as per index definition 1
14 and 2, respectively), with 0.047 being the standard deviation of index value in both cases.
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16 2) The index value for each context and time interval associated with rogue seasonality generation
17 (shaded values in Table 2) is seen to be greater than where that is not the case (unshaded values in
18 Table 2), and which is true for both index definitions. Moreover, the difference between the two is
19 significant: the average index value for the former at 1.03 and 1.17 (as per index definitions 1 and 2)
20 is greater than those for the latter by 3.6 and 4.5 standard deviation of the index value, respectively.
21 The echelon-level index therefore appears to be effective in discriminating rogue seasonality
22 generation intensity across time.
23
24 3) The correlation between index values derived on the basis of the two index definitions is seen to
25 be around 0.8. While marginally lower than that seen for the full-year data, it still enables either of the
26 two index definitions to be used.
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33 5 Managerial Implications

34 The echelon-level signature's and index's effectiveness was established (as above) with an empirical
35 context; their application in practice therefore looks promising. Their use would be particularly
36 relevant to multiple supply chain analysis contexts, including those in the retail sector, where a quick,
37 consistent and efficient identification of problematic echelon/s would be useful. This would require
38 the index to be computed for all echelons of each investigated supply chain at specified time intervals,
39 with an echelon at a certain time interval being identified as problematic, in the case that the index
40 value for it exceeded a specified threshold. Figure 6 summarises the process of practically applying
41 the index for a single supply chain.
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51 Some of the key application related considerations are:

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53 **Supply chains and products/SKU's (within each supply chain) to be considered:** While it would
54 be beneficial to include all supply chains and all products/SKU's within each, a selective focus may
55 be appropriate where there are resource constraints; only critical supply chains and key
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3 products/SKU's (within each) from a cost and customer service perspective could be considered in
4 such cases. It is important to recognise that given the many echelons in a supply chain, the volume of
5 assessments associated with echelon level sensing would be significantly more than that with the
6 supply chain level approach; the greater complexity would mean more technology and related
7 resource requirements, and therefore, resource availability constraints would be an important
8 consideration during implementation. Blackhurst et al. (2011) provide a good basis for deciding the
9 criticality of supply chains and products from a disturbance management perspective.
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14 **Time series data on system variables:** Echelon-wise data on system variables such as orders,
15 receipts, despatches and inventory for the concerned supply chains is needed for computing the
16 signature and index. Given the increasing emphasis on information exchange and collaboration,
17 further boosted by the discourse on big data and its benefits, as well as the availability of enabling
18 technologies such as RFID (Herrmann et al. 2015), this is not expected to be a significant hindrance.
19 Another requirement is for the data to be available at an appropriately sampled frequency, as dictated
20 by the Nyquist sampling theorem. While daily data, if available, would be appropriate for most cases
21 as it would be able to handle the cyclical nature of the order of 2 days or more, in the case that only slower
22 sampled data such as weekly data is available, its appropriateness vis-a-vis the context would need to
23 be assessed.
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30 **Index computation related:** There are several aspects to this:

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32 *Filtering out unrelated/irrelevant frequencies from the spectra of variables before index computation:*
33 This is important so that these (unrelated/irrelevant) frequencies, typically encountered in the low
34 frequency range on account of factors such as exogenous seasonality/long term trends, do not interfere
35 with the index's logic/validity. The cut-off for low frequency (so as to filter out all frequencies below
36 it from the spectra of all the variables) could be based on the sampling frequency: for e.g., for daily
37 data, frequencies lower than 0.03/day (or cycles of time periods greater than a month) could be
38 considered low. Further refinement could be done on the basis of previous and expert knowledge
39 about operating dynamics. Another set of (unrelated/irrelevant) frequencies needing to be filtered out
40 are those pertaining to time-batching; these could be determined on the basis of historical
41 data/patterns. Such frequencies present in the spectra of individual variables would need to be filtered
42 out from all the variables before index computation. Here all variables includes those which are
43 relevant to index computation for a particular supply chain echelon (as per the index definition).
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51 *Index as per which definition, definition 1 or 2*

52 Given that the index as per both definitions was found to be similarly effective, either could be used.
53 However, it is important that whichever is chosen is used consistently across SKU's and over time.
54 Also, the fact that the index can do the job of the signature also, i.e. discriminate presence and
55 absence of rogue seasonality, and do so more objectively, means that it alone is sufficient for sensing.
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3 The signature can however be used as a complement in select cases, especially where, detailed
4 insights such as on the nature of the endogenous cycle generated and its causal origins are needed.
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6 *Threshold index value*

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8 It is important to specify a threshold index value to classify whether an echelon is generating or not
9 generating rogue seasonality and/or for triggering of mitigation options. This can be a fixed value
10 decided on the basis of historical index values for known rogue and non-rogue seasonality generation
11 cases as was done in the case of the coffee supply chain. Alternatively, it can be dynamic such as
12 three standard deviations above the average index value for all echelons and SKU's during each
13 evaluation.
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16 *Frequency/time interval used*

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18 This could be determined based on the on the basis of the trade-off between the increased effort/cost
19 associated with more frequent sensing evaluations and the benefits from earlier detection. Another
20 factor that needs to be considered here is sensing accuracy; more frequent (or shorter time intervals)
21 sensing could mean lower accuracy/more false alarms in sensing. Here the extent of previous data or
22 the length of the rolling window is also important as seen earlier in Section 4.3.4; the goal here should
23 be to keep as short a length as gives requisite sensing accuracy.
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29 **Mitigation options after sensing:** The usefulness of echelon-level sensing of rogue seasonality is
30 dependent on how quickly and specifically countermeasures to reduce its intensity or eliminate it
31 altogether are deployed. Actions such as those proposed by Kim and Springer (2008), including
32 reducing the supply lead time or adjusting the ordering/replenishment parameters, would need to be
33 implemented. For the latter, it is important that the adjusted parameters do not have a negative effect
34 on other parts of the supply chain. In the case of supply disruption being the cause of generation,
35 goods/material flow would need to be enabled and steps taken to avoid its recurrence in the future. It
36 is important to note here that it is the echelon (rather than a supply chain) which is more practically
37 relevant both from a rogue seasonality generation as well as its mitigation perspective.
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44 **6 Conclusions**

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46 In this paper we proposed a signature and index for sensing rogue seasonality generation and its
47 intensity, respectively, at a supply chain echelon level. While the signature is based on cluster profiles
48 of variables, the index involves quantification of the same into a numerical value. Both the signature
49 and the index were found to be effective, though for the former, an additional threshold for proportion
50 of variables clustered as per Shukla and Naim (2015) may need to be specified. Their effectiveness
51 was seen over time as well; in different time interval assessments, both could discriminate intervals
52 that involved (and did not involve) rogue seasonality generation at an echelon. As a result, rogue
53 seasonality can be sensed more precisely in terms of the echelon where it is generated, its intensity
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3 and its time of generation (through choice of an appropriately short time interval for assessments).
4 This could enable specific and timely mitigative actions to be applied, and the economic
5 consequences of rogue seasonality, minimised. The signature and index are versatile vis-a-vis input
6 data and were seen to be effective with SKU level and daily sampled data. Spectra was found to be an
7 appropriate domain for representing variables when deriving the signature and index. Finally, the
8 presence of additional endogenously generated cyclicalities in variables such as time-batching (besides
9 rogue seasonality), and the need to identify and remove them in advance of the signature and index
10 assessment was highlighted.
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16 While this study has advanced the case for sensing rogue seasonality and for the sense and respond
17 approach in general, some gaps have also emerged. One of them pertains to rogue seasonality
18 generation from supply disruptions, which was observed in this study, but still requires a more
19 detailed understanding through, e.g. the use of simulation approaches. Similarly, horizontal
20 propagation of rogue seasonality, i.e. between entities at the same echelon, can be explored, since
21 only vertical propagation is examined in most studies (including this one). Another stream of research
22 could focus on time-batching and its dynamic implications, which is an infrequently discussed topic in
23 the literature. Future research would also benefit from testing the echelon-level signature and index
24 with other empirical contexts that have more echelons, and where data on multiple variables per
25 echelon is available.
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For Peer Review Only

Appendix I

Key terms and their descriptions

Term	Description
De-trending (of data)	Refers to removing/subtracting the trend (or the increasing/decreasing) component from the time series data; this component is typically determined by fitting a line (in the least-squares sense) to the data. De-trending is required to be done for all relevant variables under consideration so that their profiles (with different trends) become comparable.
Normalisation (of data)	Refers to mean centering the time series data (of a variable), i.e. subtracting the (arithmetic) mean from all values, followed by scaling or dividing all values by standard deviation of the data. Normalisation is required to be done for all relevant variables under consideration so that their profiles (with different mean levels and of different scales) become comparable.
Frequency	Number of cycles per unit time; if the length of a cycle is 2 days, frequency = 1 cycle/2 days = 0.5 cycles/day
Fourier Transformation	Technique that decomposes a time series into its constituent sinusoids (or sine waves) at different frequencies
Spectra	Amplitudes of (constituent) sinusoids at different frequencies (determined post Fourier transformation of the time series data); peak amplitude/s at specific frequency/ies reflect corresponding periodicity in the data
Filtered spectra	Spectra where some cycles (or frequencies) have been filtered out or removed; this is done by replacing the amplitude/s for those frequency/ies with 0 values
Clustering	Technique that partitions data sets (variable profiles in time/frequency domain in this case) into a small number of homogenous groups or clusters
Euclidean distance (for dissimilarity)	<p>The square root of the sum of squared differences between corresponding elements of the two relevant vectors</p> $d_E = \sqrt{\sum_{k=1}^p (x_{ik} - y_{jk})^2}$ <p>d_E = Euclidean distance x_i and y_j are p dimensional vectors</p> <p><i>For time series:</i> x_i and y_j would be the values at different time instants, and p, the total number of time instants <i>For spectra:</i> x_i and y_j would be amplitudes of the sinusoids at different frequencies, and p, the total number of frequencies If x_i and y_j are exactly similar, d_E computes to 0 indicating no dissimilarity</p>
Ward's algorithm for clustering	A popular hierarchical clustering technique where each point (time series/spectra represented as a point in multidimensional space) is merged into clusters based on their relative closeness or similarity relationships; the clusters formed are merged again on the same basis and this is repeated until there is one all encompassing cluster. Merger of clusters at every stage is done by computing the sum-of-squares variance (i.e. squares of the Euclidean distances) for all possible two cluster mergers and then going with the one with the smallest value.

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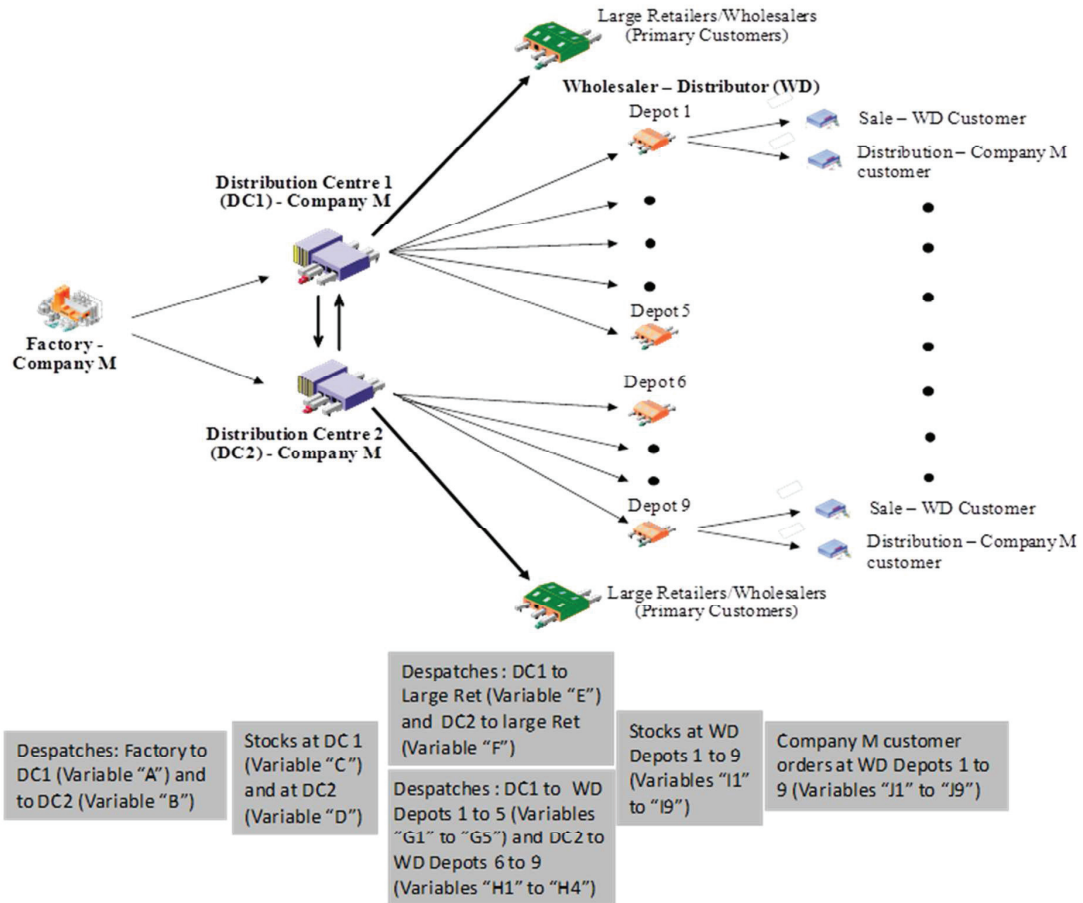


Figure 1. Downstream coffee supply chain under study and the variables considered

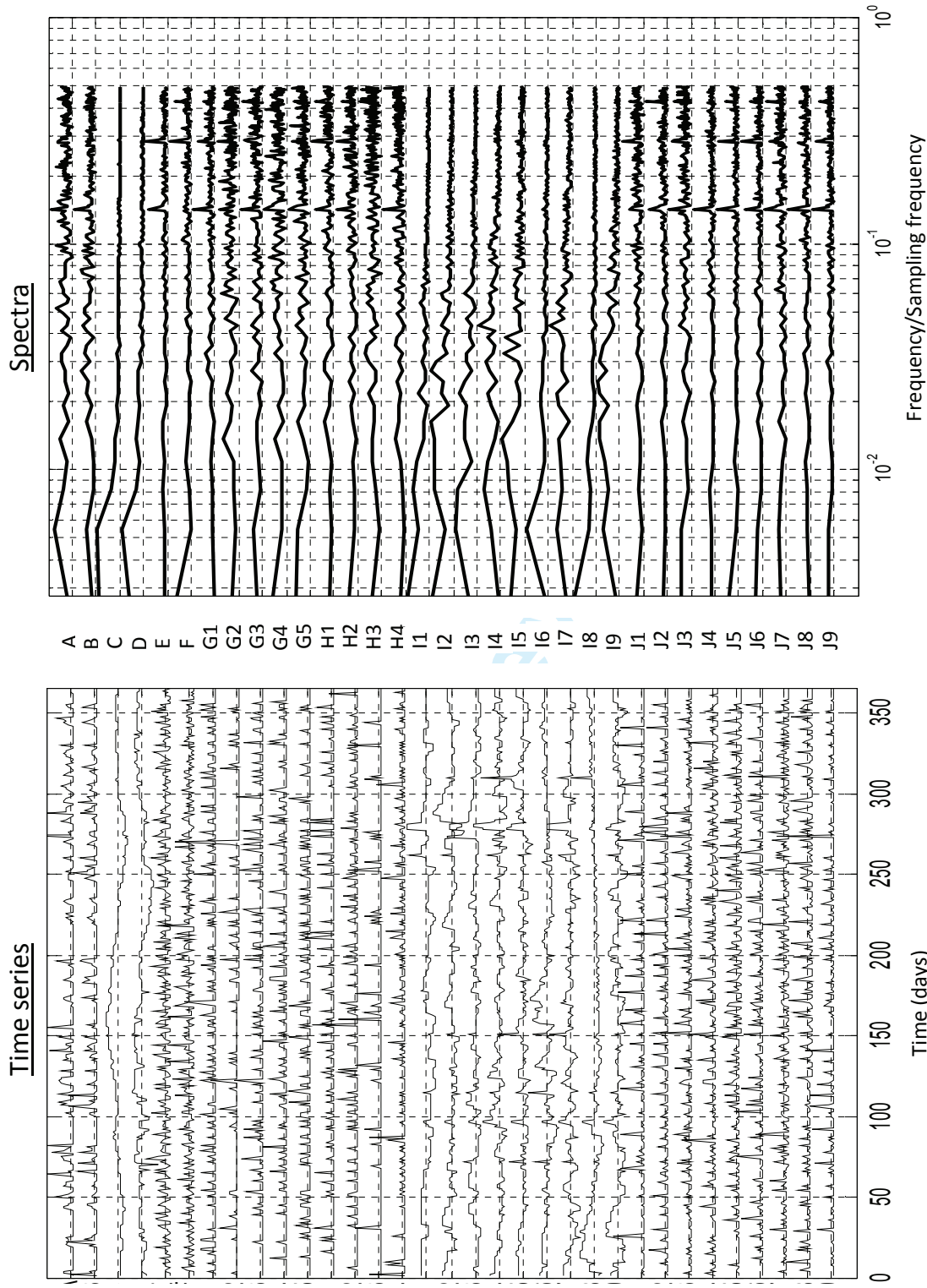


Figure 2: Time series and spectra profiles of variables for SKU1. Spectra are scaled to the same maximum peak height.

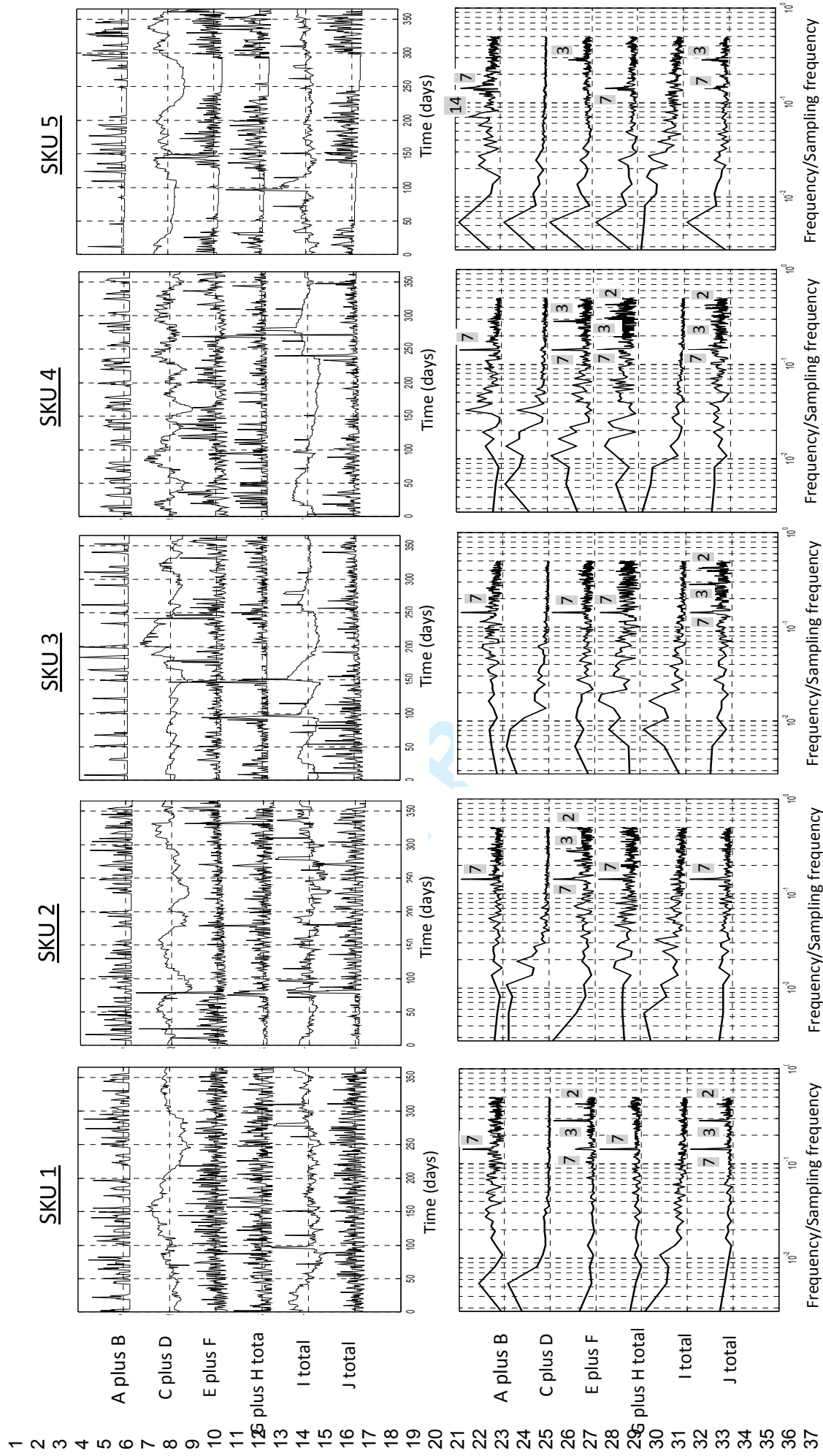


Figure 3. Time series and spectra profiles of aggregated variables for different SKUs. Spectra are scaled to the same maximum peak height.

A plus B: Total despatches from factory to DCs; C plus D: Total stocks at DCs; E plus F: Total despatches from DCs to large Retailers/Wholesalers; G plus H total: Total despatches from DCs to WD depots; I Total: Total stocks at WD depots; J total: Total company M customer orders serviced at WD depots; X: Cycle time period (days)

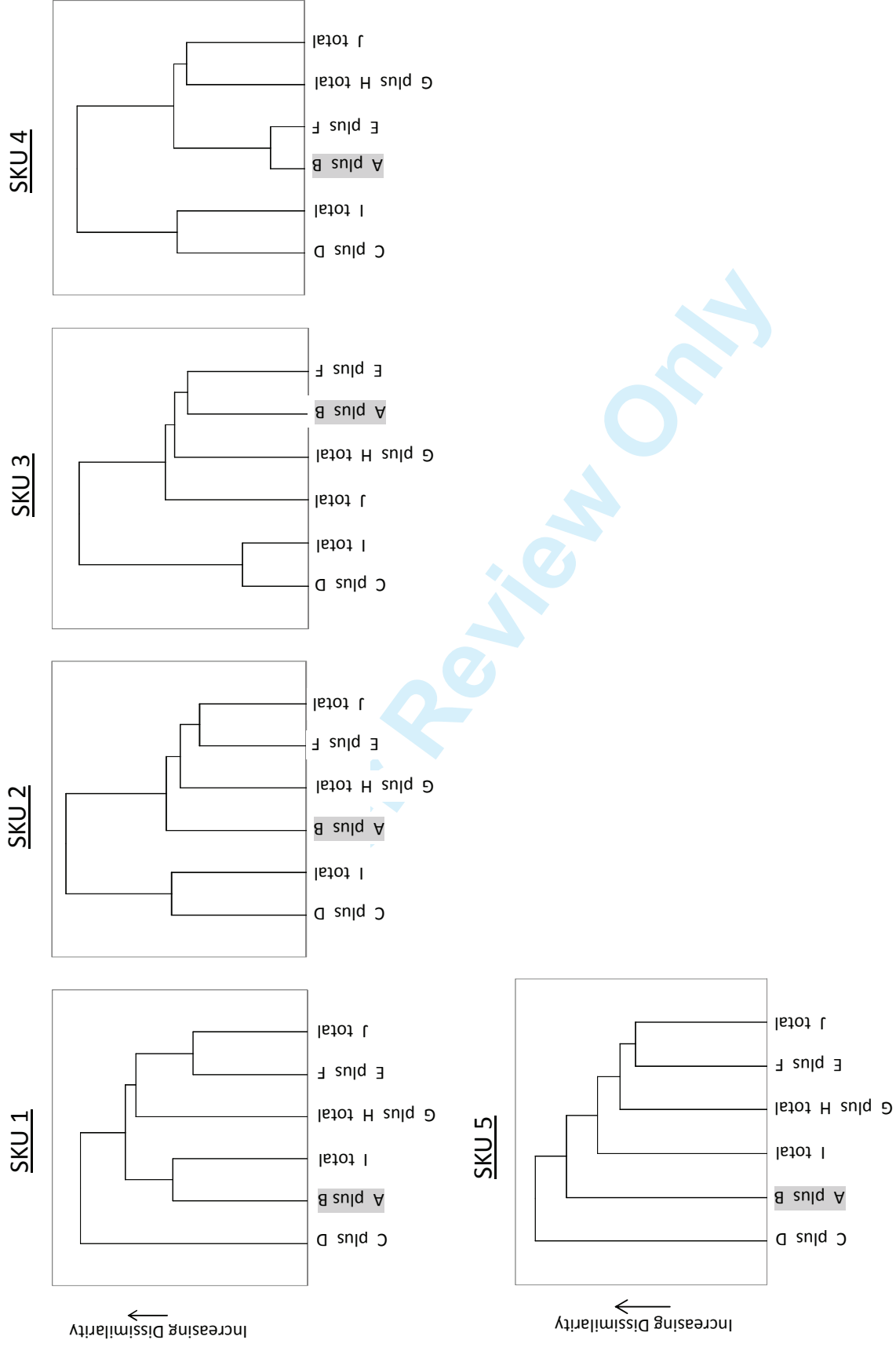


Figure 4. Cluster profiles of filtered spectra of variables for different SKUs.

Table 1

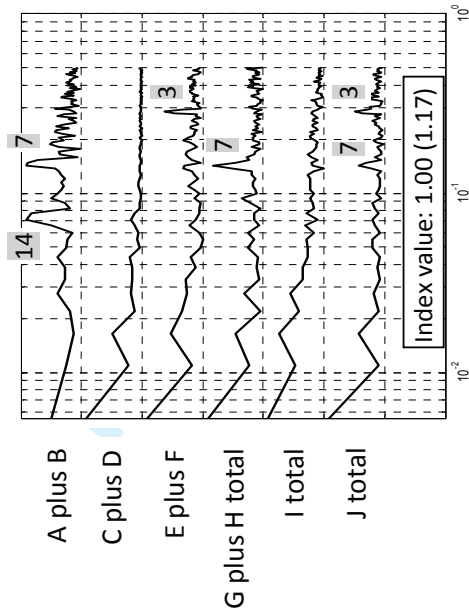
Rogue seasonality index values* at different echelons of the (aggregated) coffee supply chain for individual SKUs

At the Factory echelon		
SKU	Index value (as per index definition 1)	Index value (as per index definition 2)
SKU1	0.91	0.99
SKU2	0.93	0.99
SKU3	0.94	0.99
SKU4	0.87	0.97
SKU5	1.00	1.09
At the WD depots echelon		
SKU	Index value (as per index definition 1)	Index value (as per index definition 2)
SKU1	0.98	1.01
SKU2	0.96	1.00
SKU3	0.87	0.91
SKU4	0.90	0.98
SKU5	0.91	0.93

*Computed using filtered spectra (or amplitudes of sinusoids at various frequencies) of variables
 Avg index value (as per index definition 1) for all except shaded = 0.92
 Std deviation of index values (as per index definition 1) for all except shaded = 0.04
 Avg index value (as per index definition 2) for all except shaded = 0.97
 Std deviation of index values (as per index definition 2) for all except shaded = 0.03

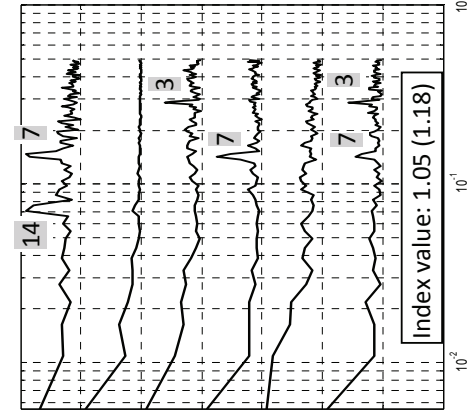
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Review at end of month 6
(Using data for months 1–6)

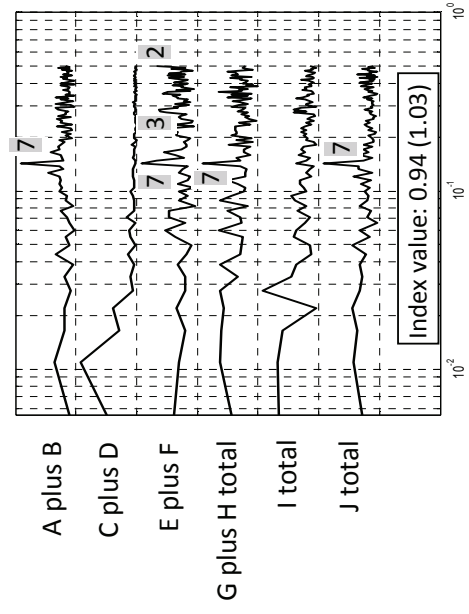
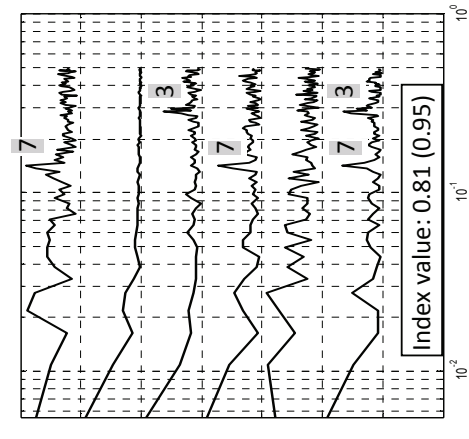


SKU 5

Review at end of month 9
(Using data for months 4–9)



Review at end of month 12
(Using data for months 7–12)



SKU 2

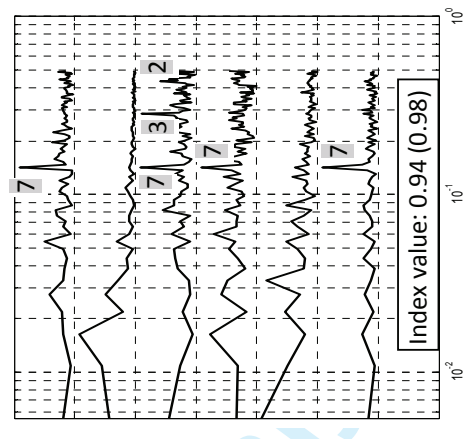
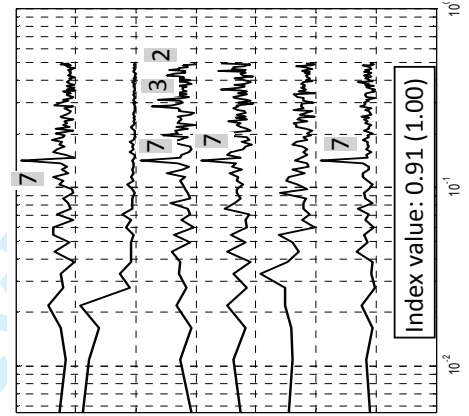


Figure 5. Spectra profiles of variables and rogue seasonality index values for the factory echelon at different time intervals. Index value A (B) implies that A is based on index definition 1 and B on index definition 2.

Table 2

Rogue seasonality index values* at different echelons of the (aggregated) coffee supply chain at different time intervals

Index value A (B) implies that A is based on index definition 1 and B on index definition 2

SKU	At the end of month 6 (Based on data for months 1–6)		At the end of month 9 (Based on data for months 4–9)		At the end of month 12 (Based on data for months 7–12)	
	At the WD depots echelon	At the Factory echelon	At the WD depots echelon	At the Factory echelon	At the WD depots echelon	At the Factory echelon
SKU1	0.91 (0.94)	0.84 (0.97)	0.80 (0.90)	0.82 (0.98)	0.78 (0.83)	0.84 (0.97)
SKU2	0.83 (0.92)	0.94 (1.03)	0.93 (0.99)	0.91 (1.00)	0.94 (0.97)	0.94 (0.98)
SKU3	0.91 (0.98)	0.90 (0.97)	0.85 (0.93)	0.81 (0.92)	0.84 (0.89)	0.83 (0.96)
SKU4	0.92 (0.93)	0.86 (1.00)	0.83 (0.93)	0.86 (1.03)	0.90 (0.95)	0.84 (0.99)
SKU5	0.88 (0.93)	1.00 (1.17)	0.82 (0.87)	1.05 (1.18)	0.87 (0.93)	0.81 (0.95)

**Computed using filtered spectra (or amplitudes of sinusoids at various frequencies) of variables*

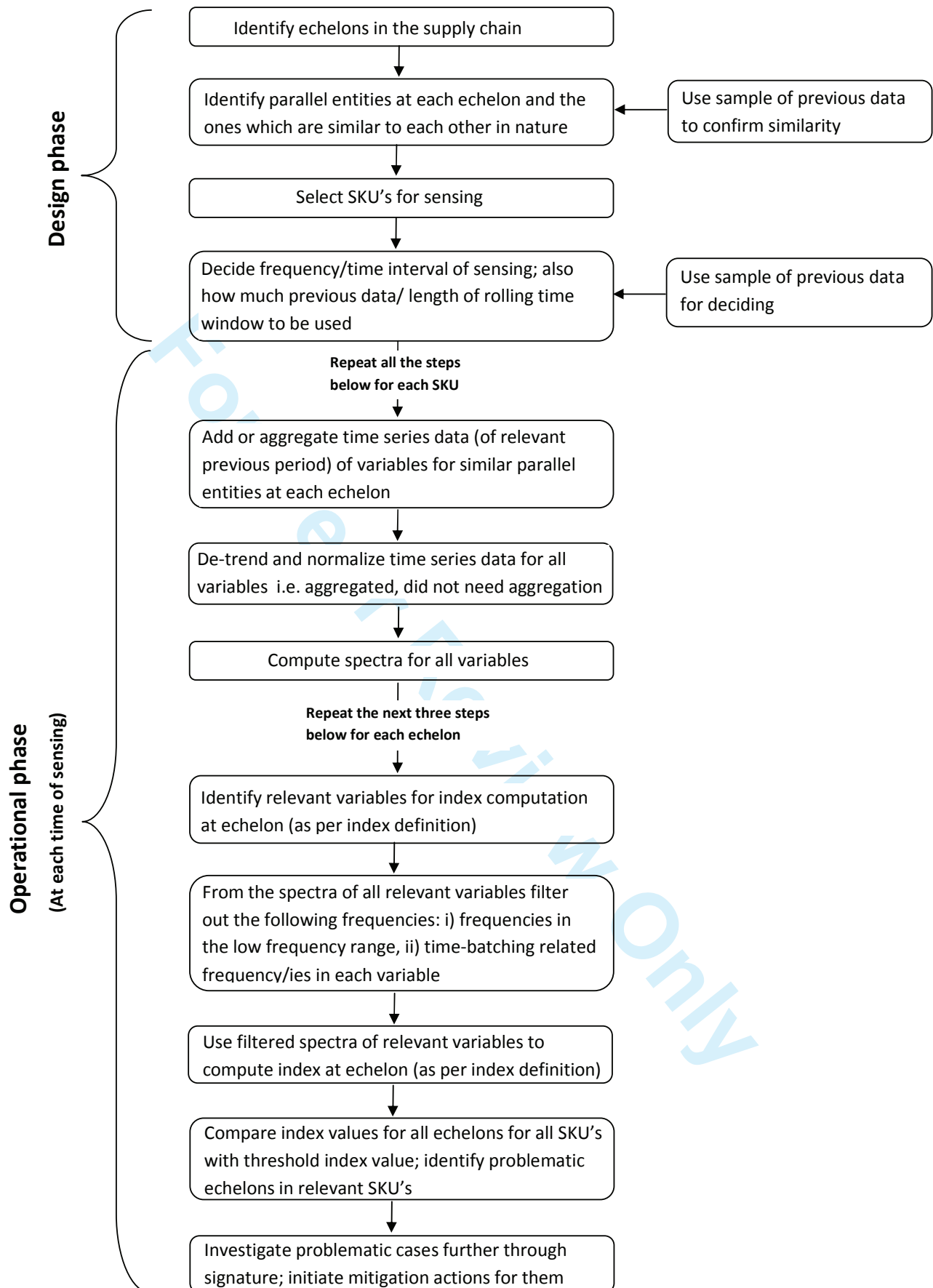


Figure 6. Flow chart for applying rogue seasonality index at a supply chain echelon level