ABSTRACT

ELAINE SYMANSKI. Time Series Behavior of Occupational Exposures (under the direction of Professor Stephen M. Rappaport).

Prior studies have observed that exposure variability increased as a function of sampling duration and attributed this phenomenon to autocorrelation. This study confirmed such behavior in occupational exposure data after controlling for factors likely to contribute to variability and assessed the impact of non-stationarity, as well as autocorrelation, on the results. Consecutive shift-long exposure measurements for 54 workers from five different data sets in 149 time series were analyzed to evaluate the variance as the interval between measurements increased. When the data were combined a clear increasing trend in the variance was observed with lag. However, a breakdown by data set revealed that the trend was present in only one of the five data sets. The effect was further isolated to 42% of the workers who contributed data and to less than 1/3 of the total number of time series analyzed. Autocorrelation and non-stationary behavior explained the increase in 60% of the time series where the trend was evident. Analysis of the entire database revealed that a small percentage of time series produced significant first-order autocorrelation coefficients or were non-stationary over the interval in which sampling was conducted. If these results are typical of other workplaces, sampling strategies may not need to address problems associated with autocorrelation or non-stationarity.

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INTRODUCTION

Exposures to airborne contaminants in the workplace vary over time and between workers. The variability in exposure can be attributed to characteristics related to the work environment such as process changes, different production schedules, or varying ventilation rates. Differences in tasks or work practices and the mobility of the worker can also influence exposure. To capture the inherent variability in exposure, air concentration can be viewed as a continuous random variable whose distribution is described by a theoretical model using a probability density function. The density function, which is typically summarized by its first and second moments, i.e., the mean, and variance, respectively, provides information about the relative likelihood of values the random variable can assume.

Historically, the lognormal distribution has been used to characterize occupational exposures. The distribution can be constructed based on information contained in a sample and used to make inferences about the underlying population of exposures. However, adequate characterization of exposures using statistical distributions relies heavily on the methods employed in the collection and analysis of the data. A campaign in which one or more measurements is collected from a few workers over a brief interval may be biased or otherwise inadequate to permit statistical inference because it might not represent the full range of exposures. Rather, a random sampling design, where a sufficient number of workers is sampled repeatedly over an adequate period of time to account for job rotation and the full range of operations giving rise to exposures, is central to the collection of unbiased data. Since such a random sample is representative of the underlying population, it should allow the distribution of exposures received by workers to be defined. Sampling strategies relying on statistical methods enhance our ability to conduct health effect studies, to evaluate appropriate control measures, and to determine compliance with exposure limits.

An often overlooked, but potentially important, aspect of exposure assessment concerns the time-series behavior of the data. Exposure data can be viewed as a set of chronological observations that may have unique properties associated with the time sequence. If the observations are a function of time, there is a relationship between present and past levels and exposures are said to be autocorrelated. If exposures are positively autocorrelated, an observation above the mean is likely to be followed by another value above the mean and vice versa, whereas negative autocorrelation arises when consecutive values alternate above and below the mean. Autocorrelated observations are no longer independent as is often required in statistical testing.

The classical model of occupational exposure views air levels as realizations of mutually independent random variables in which the serial order of the data is unimportant. In contrast, a time-series model takes the sequence of the observations into account and recognizes non-random as well as random components. Both models employ statistical techniques to evaluate the properties of the exposure distribution and allow for inferences to be made. While application of classical statistical methods to autocorrelated data might lead to erroneous conclusions, time series analysis enhances our ability to assess exposures accurately.

Three statistical properties underlie time series analysis, namely, autocovariance, autocorrelation, and stationarity. The autocovariance function describes the covariance between values in a time series and provides additional information about the second moment of the distribution. The closely related autocorrelation function measures the extent to which present values of a series are predictable from past values. Workplace scenarios depicting autocorrelation are not difficult to construct. For example, previous exposures may contribute to present levels, particularly over short sampling periods, or workplace and environmental factors may operate systematically to dominate variation in exposures day-to-day.

The concept of stationarity refers to the stability of the underlying process over time. Statistically, stationarity assumptions require unchanging mean, variance, and autocovariance functions over the period sampled, i.e., the probability laws governing the process are assumed to be constant over the interval in which data are collected or inferences are drawn. Process, production or workforce changes may influence the underlying exposure distribution and result in a non-stationary process. Non-stationary time series exhibiting changes in the mean or variance, seasonal patterns or cyclic behavior are not suitable for analysis without transformation.

Questions about autocorrelation and stationarity are important as they have implications for sampling and the assessment of dose-response relationships. Strategies to adequately assess exposures may be compromised if they are autocorrelated over time scales which exceed the period of sampling (Francis et al., 1989; Buringh and Lanting, 1991). Likewise, non-stationary behavior can undermine the process of estimating parameters of the exposure distribution (Roach, 1990). Finally, more variability in exposures is likely to be transmitted to the body burden when air concentrations are autocorrelated than when levels are purely random. Such an increase in the variance of the series of burdens may be important if damage is induced by some non-linear process (Rappaport and Spear, 1988).

Autocorrelation and stationarity are difficult to assess because they require relatively long strings of consecutive measurements. This has led to a paucity of studies which have addressed the issues directly (Francis et al.; 1989, Roach, 1990). Given the lack of suitable data, investigators have developed indirect methods to approach the problem. For example, a recent study advanced such techniques by looking at exposure variability as a function of sampling duration (Buringh and Lanting, 1991). That investigation suggested that the variance of occupational exposures, in a variety of industries, was greater when based upon intra-week as opposed to inter-week measurements. The purpose of this study is to determine whether such variance increases can be confirmed in occupational exposure data after controlling for a number of factors (data set, worker, and number of measurements) which were not considered in the study of Buringh and Lanting (1991). If such behavior is revealed, then assumptions related to stationarity and autocorrelation will be examined to determine the cause.

TIME SERIES ANALYSIS

Historically, the 2-parameter log-normal density function (hereafter referred to simply as a 'log-normal' distribution) has been used to describe occupational exposures and is given by:

$$f(x) = \frac{1}{x\sigma_y\sqrt{2\pi}} \exp\left[-\frac{1}{2\sigma_y^2}(\ln(x) - \mu_y)^2\right] \qquad \text{where } x > 0,\ -\infty < \mu_y < \infty, \text{ and } \sigma_y > 0.$$

The parameters of the log-normal distribution refer to the mean (μ_y) and variance (σ_y^2) of the transformed random variable, $Y = \ln(X)$.

Application of the log-normal distribution to workplace exposures was reviewed by Rappaport (1991) who provided empirical and theoretical evidence supporting such use when data are properly collected. However, the mean and variance provide an inadequate summary of the distribution if exposures are correlated. A third parameter, the autocovariance function, is necessary to define the covariance between any two observations in time. When the autocovariance function is standardized by the variance, the autocorrelation function is produced. The autocorrelation function describes the proportion of variability that can be attributed to the covariance between sequential observations. Estimates of the autocovariance and autocorrelation functions are the primary tools to evaluate the serial correlation of exposure data and can be used to identify the appropriate time series models for further analyses.

Trends, cycles, and seasonal variations, along with random fluctuations, are typical sources of variation in a time series. A trend is an upward or downward pattern that manifests itself as a long-term change in the mean level. Technological changes in the industrial process and changes in the rates of production can produce such trends (Esmen, 1979; Ulfvarson, 1983). Cycles represent long-term oscillations repeated over time periods of differing lengths, usually longer than one year. If an industrial operation is well controlled and intermittent in nature, exposures could mimic the process closely resulting in cyclical behavior. Seasonal effects represent fluctuations occurring within a fixed period of one year. They are typically caused by factors such as weather (e.g., opening and closing windows) and prevailing winds. Trends and seasonal or cyclical variations do not occur by chance, but reflect deterministic factors. Irregular fluctuations, which follow no recognizable pattern, are also observed in exposure data. Thus, time series analysis involves decomposing the sources of variation into its deterministic and random components and modeling the stochastic element.

Properties of Time Series

Time series models are built upon stochastic processes. A stochastic process is a collection of time-ordered random variables and can be specified by the joint distribution of $\{X_t\} = X_{t_1}, X_{t_2}, \ldots, X_{t_n}$ for any set of times t_1 through t_n. Each random variable at any time t is defined by a probability density function describing the relative likelihood of all possible values. Thus the behavior of a sequence of random variables defining the stochastic process will be determined from a multivariate joint distribution. Although explicit characterization of the multivariate distribution is difficult, it is straightforward to describe its parameters. For a stochastic process, the mean, variance, and autocovariance functions are defined as follows (Chatfield, 1989):

$$\mu(t) = E(X_t)$$

$$\sigma^2(t) = Var(X_t) = E(X_t - \mu(t))^2$$

$$\gamma(t_1, t_2) = Cov\left(X_{t_1}, X_{t_2}\right) = E\left\{\left(X_{t_1} - \mu(t_1)\right)\left(X_{t_2} - \mu(t_2)\right)\right\}$$

An observed time series is only one realization of the process from an infinite number of time series (called the ensemble) which could have arisen. In time series analysis, inferences are made from a realization of the stochastic process in much the same manner that inferences in classical statistics are made from random samples. In order to make inferences, the underlying process must be ergodic and stationary. Ergodic theorems state that for stationary processes (to be defined shortly), the parametric estimates obtained from a single realization are reliable estimates for the entire ensemble (Granger and Newbold,1986). Ergodicity implies that averages obtained from a single realization through time converge to the ensemble averages (Chatfield, 1989). Using the average over time as an example, the values of an ergodic process separated by large enough intervals show little autocorrelation and thus add useful information in estimating the mean. Therefore,

$$\bar{x}_n = \frac{1}{n}\sum_{t=1}^{n} x_t$$

is an unbiased and consistent estimate of the population mean, i.e., $E(\bar{x}_n) = \mu$ and the variance of the estimate, $Var(\bar{x}_n)$, goes to zero as n goes to infinity. Ergodic theorems also apply to the variance and the autocorrelation functions.

Stationarity

A time series $\{X_t\}$ is said to be strictly stationary if the joint distribution of $\{X_{t_1}, X_{t_2}, \ldots, X_{t_n}\}$ is the same as the joint distribution of $\{X_{t_1+k}, X_{t_2+k}, \ldots, X_{t_n+k}\}$ for all values of t and time lag k. If a time series is strictly stationary, the distribution function is the same at every point in time and depends only on the interval between observations (i.e., the lag) and not on the actual values. This implies that shifting the time origin by k has no effect on the joint distribution and that the covariance function depends only on the lag.

Strict stationarity can not be confirmed in practice since knowledge of the complete distribution function is impossible. A less formal and mathematically weaker definition deals with the first two moments of the time series. Specifically, a time series is weakly or second-order stationary if $\mu(t)$ is equal to a constant, μ, for all t, i.e., there is no trend, and the covariance matrix of $\{X_{t_1}, X_{t_2}, \ldots, X_{t_n}\}$ is the same as the covariance matrix of $\{X_{t_1+k}, X_{t_2+k}, \ldots, X_{t_n+k}\}$. Thus, for a time series which is second-order stationary, the covariance between two random variables is a function only of the lag. The autocovariance function, $\gamma(t, t+k)$, is therefore expressed by:

$$\gamma(k) = Cov(X_t, X_{t+k}) = E\{(X_t - \mu)(X_{t+k} - \mu)\}$$

The Autocorrelation Function

If the joint distribution of $\{X_{t_1}, X_{t_2}, \ldots, X_{t_n}\}$ is multivariate normal for all $t_1, \ldots, t_n$, then the process is completely specified by its first and second moments, i.e., by $\mu(t)$ and $\gamma(t_1, t_2)$. The autocorrelation function, $\rho(k)$, measuring the relationship between any two observations in a time series, X_t and X_{t+k} and separated by a lag of k time units is given by:

$\rho(k) = \gamma(k)/\gamma(0)$ where $\gamma(0)$ is the variance.

Some important properties of the autocorrelation coefficient include:

1) $-1 \leq \rho(k) \leq 1$,

2) $\rho(0) = 1$,

3) $\rho(k) = \rho(-k)$, and

4) if X_t and X_{t+k} are independent, then $\rho(k) = 0$.

<u>Estimation of Autocorrelation Function</u>

Sample statistics can be computed from time series data. The sample autocovariance as a function of lag k, c_k, can be computed by:

$$c_k = \frac{1}{N}\sum_{t=1}^{N-k}(x_t - \bar{x})(x_{t+k} - \bar{x})$$

The sample autocorrelation coefficient, r_k, is estimated from the data according to the following equation:

$$r_k = \frac{\sum_{t=1}^{N-k}(x_t - \bar{x})(x_{t+k} - \bar{x})}{\sum_{t=1}^{N}(x_t - \bar{x})^2} = \frac{c_k}{c_0}$$

Autocorrelation coefficients are not reliable for values of k larger than 25% of the series length (Chatfield, 1989).

In order to determine whether there is any evidence of serial dependence, r_k is plotted against k in a graph called the correlogram. For a random series (a 'white-noise' sequence) and large n, the autocorrelation coefficient is normally distributed with mean zero and variance $1/n$ (Diggle, 1990). Thus, an approximate 95% confidence interval of the autocorrelation function can be found by:

$$-1/n \pm 2/\sqrt{n}$$

In practice, the calculation of the interval is simplified to $\pm 2/\sqrt{n}$, representing two standard errors from the mean.

Caution must be exercised when interpreting the correlogram because the probability of obtaining a coefficient significantly different from zero increases with the number of coefficients.

Secondly, if only one or two coefficients is significant, the magnitudes and lags of the coefficients must be considered when determining whether a time series is autocorrelated (Chatfield, 1989). Coefficients far outside the confidence limits suggest an autocorrelated time series as do 'significant' coefficients at lags that have some physical interpretation.

The pattern of the correlogram can also provide valuable information about the underlying process (Chatfield, 1989). Autocorrelation coefficients decaying exponentially suggest a first-order autoregressive process whereas a drop of the autocorrelation function to zero after lag one indicates a first-order moving average process. It may be difficult, however, to distinguish between exponential decay and zero autocorrelation if the sample isn't very large. The correlogram may also be useful in identifying non-stationary behavior if the series of coefficients decays slowly.

Transforming Non-stationary Series

Non-stationary time series exhibiting changes in the mean or variance or seasonal or cyclic behavior must be transformed before they can be analyzed. Various methods are available to transform the data and include constructing moving averages, fitting a polynomial to the data, and differencing. Although a large part of time-series analysis is devoted to transforming a non-stationary series into a stationary series, recognizing non-stationary behavior may be more important in exposure assessment than applying methods to make the data suitable for subsequent analysis.

Differencing is typically used to remove a trend and to make a time series stationary. First-order differencing removes linear trends. The first difference for a time series $\{X_t\}$ for (t_1, t_2, ... t_n) defines a new time series $\{D_t\}$ for (t_0, t_1, ... t_{n-1}) where:

$$d_t = x_{t+1} - x_t = \nabla x_{t+1}$$

The transformed variable has a different interpretation because it estimates the rate of change of the data. First differencing will not eliminate higher-order trends. For example, if a quadratic trend is present, the time series must be differenced twice (i.e., the series of first differences is also differenced).

The autocorrelation function of the differenced data will rapidly decay to zero if the original time series consists solely of a trend and of a stationary stochastic process. In practice, removal of a trend may induce spurious autocorrelation into the residual sequence so interpretation of the transformed series for autocorrelation can be limited (Diggle, 1990).

Time-Series Models

Several probability models have been developed to represent different types of stochastic processes underlying stationary time series. Two useful models rely on autoregressive (AR) and moving average (MA) processes. An autoregressive model of order p, abbreviated AR(p), expresses a current value in a time series as a function of p preceding values plus random error. The dependent variable is regressed on previous values rather than on independent variables as in a regression model. MA models relate the current time series value to the random errors from preceding time periods rather than to previous values as in AR processes. Combining characteristics from both AR and MA processes defines another set of models for time-series analysis, the autoregressive moving average (ARMA) models. These models all exhibit non-zero autocorrelation.

APPLICATIONS OF TIME-SERIES ANALYSIS TO OCCUPATIONAL EXPOSURES

The first-order autoregressive process (AR(1) process) has been used to describe occupational exposures where current values are expressed as a weighted function of the previous exposure plus random error (Roach, 1977; Spear et al., 1986; Preat, 1987; Rappaport and Spear, 1988; Francis et al., 1989). The model can be specified as follows:

$$X_t = \alpha X_{t-1} + Z_t$$

where X_{t-1} and X_t are sequential air concentrations, α is the autocorrelation parameter, and Z_t is a variable from a purely random process with mean zero and variance σ_z^2. The mean and variance of X_t are given by:

$$\mu = E(X_t) = 0$$

$$Var(X_t) = \sigma_x^2 = \sigma_z^2/(1-\alpha^2)$$

The autocorrelation function is:

$$\rho(k) = \alpha^k \text{ for } k > 0.$$

Short-Term Exposures

The issue is to determine whether occupational exposures are correlated and to apply the appropriate probabilistic model. A review of the literature suggests that very little data is available to answer this question (Rappaport, 1991). Some of the earliest work identified time-dependent, non-random factors influencing occupational exposures measured continuously over short intervals (Coenen, 1971; Roach, 1977). Theoretical models suggest that significant autocorrelation is likely with intra-shift exposures. Roach (1977), Spear et al. (1986) and Rappaport and Spear (1988) derived expressions for the autocorrelation coefficient as a function of the air-exchange rate in short-term data.

The parameters of distributions of short-term autocorrelated measurements have been related to the parameters of distributions of exposures that have longer averaging times (Coenen, 1971; Spear et al., 1986; Preat, 1987). Coenen (1971) expressed the variability of long-term measurements as a function of short-term variability, the number of short-term intervals in the longer sampling period, and a 'measure of autocorrelation'. Spear et al. (1986) built upon this model by defining the autocorrelation function more explicitly. Preat (1987) derived similar relationships between variances of distributions with different averaging times using methods developed for geostatistics. These relationships show that the means of the short- and long-term distributions are the same but that the variances are not. The variance tends to increase as the averaging time decreases. Secondly, the variance of shift-long exposures is larger when the shorter-term measurements are serially correlated than it would be in the absence of any autocorrelation.

Long-Term Exposures

Assessing correlation in day-to-day exposures has been more problematic. The influence of autocorrelation in estimating the parameters of a distribution of day-to-day exposures was explored by Francis et al. (1989). Three exposure distributions were simulated using a 1st-order autoregressive model with the same mean and variance but with different levels of autocorrelation. In analyzing sets of five sequential time-measurements sampled from each distribution, they found that higher levels of autocorrelation were more likely to result in less precise estimates of the mean and to underestimate the variance. Their findings have particular implications to sampling campaigns restricted to periods of a week or less where autocorrelation may be more likely, although it may be prudent to consider serial correlation in data collected over longer periods of time.

Workplace or environmental factors likely to systematically influence shift-long exposures have been identified (Esmen, 1979; Ulfvarson, 1983; Buringh and Lanting, 1991). Esmen (1979) observed a higher correlation between exposures resulting from batch processes than with continuous operations. Ulfvarson (1983) observed a relationship between production and exposure in the dry-cleaning and metal industries where higher productivity levels mid-week were accompanied by higher exposures. The influence of seasonal effects on exposures in outdoor workplaces has also been noted (Ulfvarson, 1983; Buringh and Lanting, 1991).

Evaluating autocorrelation explicitly has been more difficult since it requires the collection of relatively long strings of sequential measurements. Francis et al. (1989) conducted the only study to deal with the question directly by performing time-series analysis of occupational data sets. Their results suggested relatively few instances where the first-lag autocorrelation coefficients were significant.

Buringh and Lanting (1991) evaluated exposure variability in data collected over different sampling periods. They observed that variance estimates in data collected within a week were smaller than those from data collected over longer intervals and attributed this to serial correlation. The authors also argued that their results, coupled with the limited resources usually available for sampling, provided a rationale for 'worst-case' sampling strategies. This recommendation is in stark contrast to arguments in favor of strategies based on statistical approaches rather than on conventional methods (Rappaport, 1991).

<u>Analysis of the Study of Buringh and Lanting</u>

The study of Buringh and Lanting (1991) deserves close scrutiny given the far-reaching conclusions of the authors. The analysis was based on a large number of data sets (420) from indoor workplaces. Personal exposure measurements were used, ranging between 3 to 13 observations per set. The data were assembled into two groups according to the time interval over which the observations were collected; 249 sets of measurements were collected within a week and 171 sets spanned more than a week.

When the mean geometric standard deviations (GSDs) for the two groups of data were compared a larger value was observed for the group containing sets collected between weeks. A computer simulation was also conducted in which 10,000 data sets, proportional in size and number to the original data, were drawn equally between a random series and a series following an autoregressive process ($\rho(1)=.8$). The distribution of the GSDs from the simulated data approximated the values obtained from the actual data. The authors concluded that the workplace exposures were probably autocorrelated.

A major drawback in the analysis conducted by Buringh and Lanting was the lack of control for factors likely to contribute to variability. These factors include industry, location, type of exposure, worker, and number of measurements per sample. Although the data spanned a wide cross-section of industries, they were not equally represented between the two groups constructed for comparison. In some instances, data from certain industries contributed exclusively to one group. For example, data from a battery factory, a printing office, automobile factories, powdered-soap factories, and dry-cleaning shops contributed entirely to the group whose measurements were collected within a week.

The data were also disproportionately distributed by industry. Notable was the preponderance of data from the cattle-feed industry (approximately 60%) in the group of data collected over the longer time period. An unequal breakdown by type of exposure also characterized the two groups. For example, dust was the predominant exposure evaluated in the data collected over longer sampling periods (78% of the measurements) compared to the other group (42% of the measurements).

Failure to control for worker may also have confounded the findings. Exposure variability can be partitioned into two components, a component associated with time (day-to-day variability) and a component associated with worker (between-worker variability). The between-worker component can be relatively large among some groups making it an important source of variation (Rappaport, 1991; Rappaport, et al., submitted, 1992). In those cases where the same workplace but different workers contributed data in the groups constructed for comparison, it is impossible to isolate the day-to-day component of variance, which is needed for such comparisons, from the total variance in exposures (sum of within and between components).

Given the lack of control for worker, industry, location, and type of contaminant, the observed increase in the variance estimates with sampling period might be a spurious finding or might not be the result of autocorrelation as suggested by the authors. Since some of the data used in the analysis was collected over periods of months, a question is raised about the stationarity in the underlying process giving rise to exposure. Decreasing or increasing trends in exposures due to process or production changes, for example, would be masked entirely since relatively few measurements were collected. Yet such trends could contribute to large but unstable variance estimates. It becomes particularly relevant to the analysis if a workplace contributed data to both groups, reflecting a stationary process within a week but non-stationary conditions over the longer time interval.

Perhaps less important are questions that relate to size differences between the data sets used to construct the comparison groups. At the first level of analysis, the precision of the variance estimates varied among data sets according to sample sizes which ranged between 3 to 13 measurements. The group containing data within a week was almost 1 1/2 times larger than that containing data between weeks so the precision of the estimates could have differed. Lastly, since the standard errors of the estimates were not provided, it is difficult to determine if the differences were significant.

In conclusion, several questions are raised regarding the study of Buringh and Lanting (1991). Was the analysis rigorous enough to support conclusions that intra-week exposures were likely to be significantly autocorrelated? If not, how could the design of a study be improved to determine if day-to-day variability in exposures increases with the sampling period? And, finally, if the observed effect is real, how might autocorrelation and non-stationarity be evaluated as contributors to the apparent trend?

The primary purpose of this investigation is to determine if day-to-day variability in exposures increases with the interval over which sampling is conducted. A secondary purpose is to assess non-stationarity and autocorrelation as possible explanations for any observed increase in variance with sampling duration. The study is designed to control for the industry, location, and worker and to address some of the shortcomings evident in the study of Buringh and Lanting (1991).

METHODS

A database has been constructed of approximately 20,000 exposure measurements collected by personal sampling from workers in a broad cross-section of industries worldwide (Kromhout et al., in preparation, 1992). In addition to air concentrations, the database recorded industry, process, production, sampling, and workplace characteristics for each data set. The database was accessed to identify workers who contributed at least 30 consecutive measurements. Fifty workers from five data sets met this criterion. To address problems with missing data and periods of non-exposure due to absences, intervals of up to seven days between sequential measurements were permitted; however most sequences had measurements no more than one or two days apart.

The breakdown of data by industry appears in Table 1. There were four workers exposed to alkyl lead and inorganic lead in an alkyl manufacturing plant, 28 workers exposed to an organic vapor at a pesticide-production facility, 15 workers exposed to inorganic mercury in a chloralkali- processing plant, and 3 workers exposed to isopropyl alcohol in an automobile-manufacturing plant. Twenty-five workers (23 from the pesticide-manufacturing plant and two from the automobile-manufacturing plant) were sampled over longer intervals and contributed multiple time series. In nine instances, data were so extensive that six to 14 strings (30 measurements per string) per worker were constructed. Overall, there were 149 time series analyzed in the study.

Table 1. Breakdown of the data analyzed in the study.

Data Set	Exposure	No. of Workers	No. of Time Series
Alkyl Lead Manufacturing Plant	Alkyl Lead	4	4
Alkyl Lead Manufacturing Plant	Inorganic Lead	4	4
Pesticide-Production Facility	Organic Vapor	28	120
Chloralkali-Processing Plant	Inorganic Mercury	15	15
Automobile-Production Plant	Isopropyl Alcohol	3	6
Total:		54	149

For each time series, the natural logarithms of the air concentrations were computed, i.e., $y_n = \ln(x_n)$ for $(n_1, n_2, \ldots, n_{30})$. Pairs of measurements (log-transformed data) were obtained at a lag of 1 to 10 days. The lag period dictated the number of pairs that could be formed. For example, 29 pairs separated by one day could be constructed from a string of 30 measurements by coupling consecutive values (y_n, y_{n+1}) for n=1 to 29. Only 20 pairs could be assembled when lagging values by 10 days (y_n, y_{n+10}) for n=1 to 20. Twenty pairs of measurements were randomly selected for each lag period (except for lag 10) so that an equal number of data points for each lag contributed to the analysis. In total, there were 200 pairs of measurements associated with each time series grouped by the number of days separating each pair. At each lag, the mean value of the variances (S_y^2) for the 20 pairs was computed. The number of days separating each pair was also averaged by lag period to assess any unevenness in the spacing of the data.

The relationship between the variance and lag was first examined by combining the data from all data sets. Subsequent analysis investigated the mean variances by industry, followed by workers in a given industry, and by individual time series by worker in a given industry. Each level of analysis included plots of the mean value of the variance by lag period. It was of interest to note what patterns changed in the plots as the level of analysis was broken down by factors likely to contribute to variability.

Time series plots were visually examined to detect changes in the mean or variance or any cyclical behavior. Two autocorrelation analyses were performed using SAS ETS statistical procedures (SAS Institute, Cary, N.C., 1992). The correlograms were initially inspected to identify plots where the coefficients decayed slowly to zero suggesting an underlying non-stationary process. To be less subjective and more rigorous in assessing stationarity, the test of the unit-root hypothesis, a formal test of stationarity, was applied using SAS ETS statistical procedures. These procedures rely upon the work of Dickey and Fuller (1979) and Said and Dickey (1984). The test assumes that an autoregressive or mixed model explains the underlying process. For an AR(1) process, the test regresses the first difference on the residuals of the lagged values adjusted by the mean and can include a predictor variable for time if the data appear to have a linear trend. The statistic for the estimate of the parameter for the residual term provides the statistical test for stationarity and has a distribution derived by Fuller (1976). The null hypothesis assumes non-stationarity so constraints by sample size may limit the power to reject non-stationarity. To investigate this possibility, longer time series, ranging in size from 61 to 143 measurements, were constructed and examined for non-stationarity.

Non-stationary series were transformed by differencing to attempt to remove linear trends in the data. The differenced series were examined visually and reanalyzed for stationarity and autocorrelation. Correlograms were generated and examined to determine if any coefficients were significant at the approximate 95% confidence level (exceeding $\pm 2/\sqrt{n}$).

RESULTS

Variance versus Lag

The results comparing variance to lag for each separate analysis appear in Table 2. Overall, the variance increased with lag when data from the five data sets, comprised of 54 workers and 149 time series, were combined. The analysis by data set, however, revealed that this effect was present in only one of the five sets, namely that from the pesticide production facility. Finally, it was further demonstrated that the trend was evident in only 1/3 of the time series analyzed among the pesticide workers.

Table 2. Percentage breakdown from the analysis relating variance to lag by set, worker, and time series.

Data Set	Trend Between Variance and Lag?	% of Workers Displaying a Trend*	% of Time Series Displaying a Trend*
Alkyl Lead Manufacturing Plant (alkyl lead)	No	0 (0/4)	0 (0/4)
Alkyl Lead Manufacturing Plant (inorganic lead)	No	0 (0/4)	0 (0/4)
Chloralkali-Processing Plant	No	13 (2/15)	13 (2/15)
Automobile-Production Plant	No	33 (1/3)	17 (1/6)
Pesticide-Production Facility	Yes	64 (18/28)	35 (42/120)
Total:		42 (21/54)	30 (45/149)

* Actual numbers out of the total are given in parentheses.

Figure 1 plots the variance versus lag when all of the data is combined. The variance ranges from about 1.4 to over 2.0 with a clear increasing trend between variance and the lag period separating pairs of measurements. This result is consistent with the major finding observed in the study of Buringh and Lanting (1991).

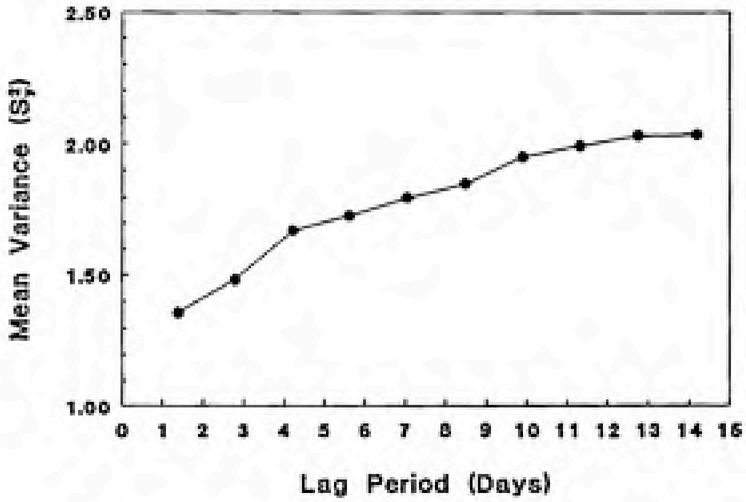

Figure 1. The variances between 2,980 pairs of log-transformed data were averaged at each lag period (20 pairs/lag from each time series; 149 time series in total from 5 data sets).

A breakdown by industry, however, quickly changes the interpretation of the data and becomes extremely informative. Graphs for each of the five data sets are plotted in Figure 2. Of the five data sets, only the pesticide-production facility shows a trend between the mean variance and the lag. The alkyl lead manufacturing plant (alkyl lead and inorganic lead), the chloralkali-processing plant, and the automobile-manufacturing plant data display no increase in the mean variance with lag. These four data sets are characterized by relatively stable variances as the lag increases, although the variance fluctuates slightly in alkyl lead exposures at the lead manufacturing plant. In contrast, the pesticide-production facility data exhibits a significant increasing trend between variance and lag. Air concentrations are highly variable, with mean values for the variance among pairs of measurements from approximately 1.6 at lag 1 to around 2.4 at lag 10. These results indicate that the trend observed in the combined data sets (Figure 1) arose in fact from the contribution of the pesticide-production facility.

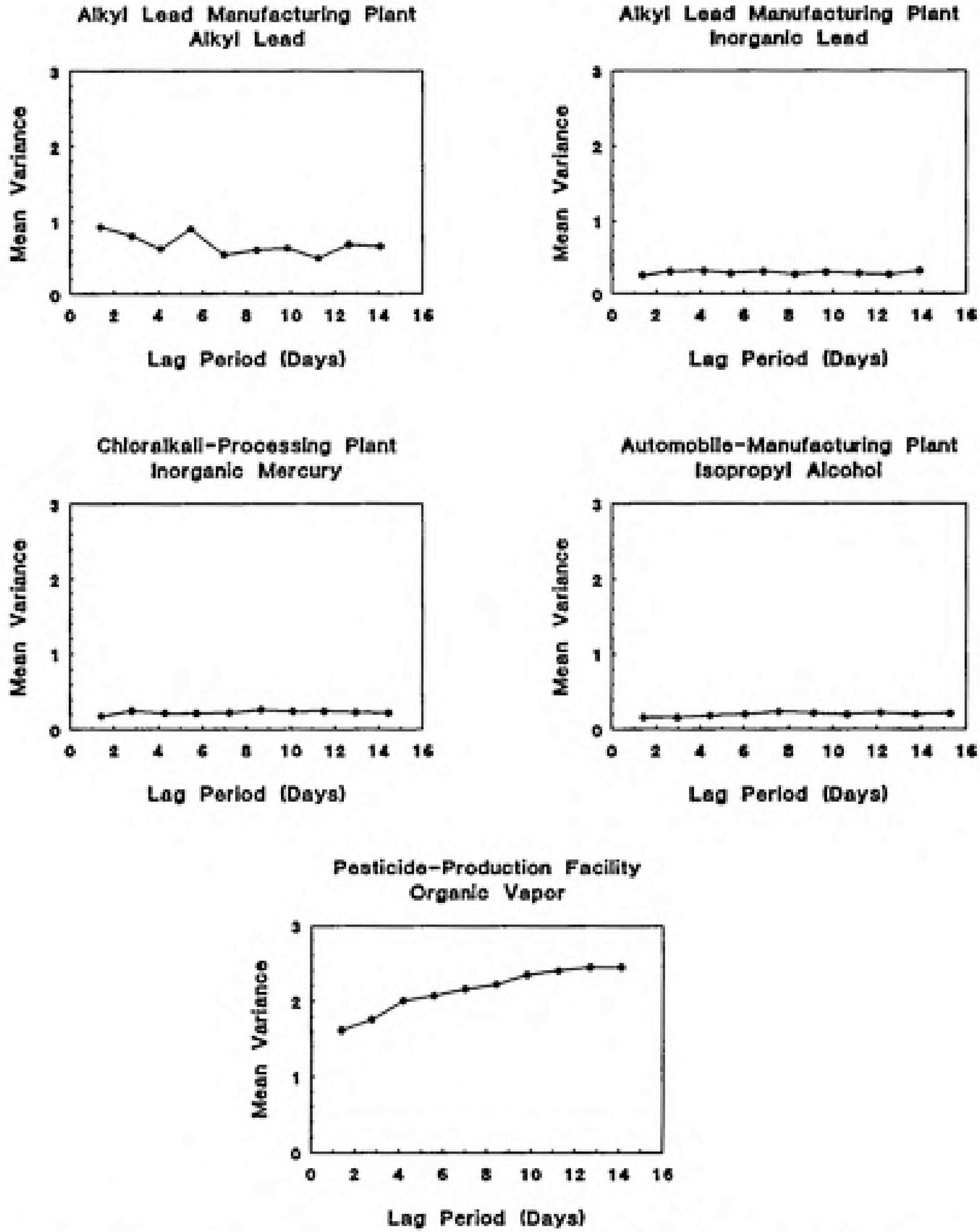

Figure 2. Plots of mean variance (average of S_y^2 for log-transformed data) vs. lag by data set.

In an effort to further isolate the effect, data for each worker was assessed separately. None of the data from the lead-manufacturing plant showed a discernible pattern between variance and lag. Two plots shown in Figure 3 provide an illustration of the lack of trend between variance and lag in the data generated at this facility. Graph A depicts data from Worker 4 exposed to alkyl lead while Graph B plots the inorganic lead data for Worker 3. Both of these plots appear erratic and are characterized by mean variances that fluctuate randomly with lag.

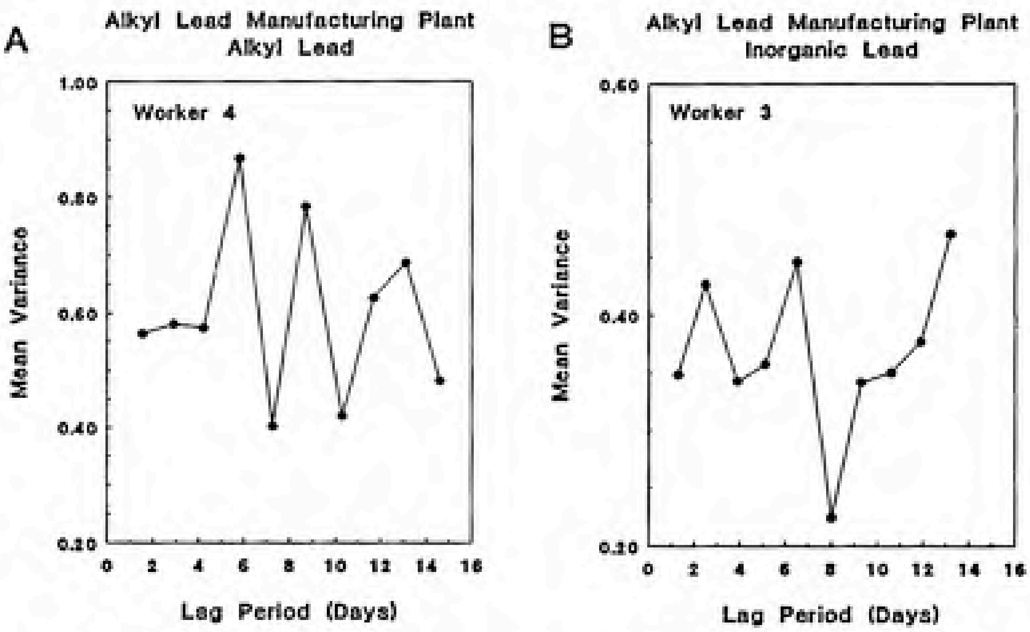

Figure 3. Plots for two workers at the alkyl lead manufacturing plant. Mean variances (average of S_y^2 for log-transformed data) in both plots appear to fluctuate randomly with lag.

Of the remaining data sets, 21 of 46 workers exhibited a trend of increasing variance with lag. This included 18 workers from the pesticide plant (64% of the workers in this data set), two from the chloralkali plant (13%), and one from the automobile plant (33%). To contrast plots of variance that increase with lag from those that show no trend, data from representative workers from these three facilities appear in Figures 4-6. Graph A in each figure depicts no trend whereas graph B does. The data for Worker 15 in Figure 4-B at the pesticide plant is characterized by extremely large and variable exposures, ranging from about 1.6 to over 3, whereas the values for the other two workers (Figures 5-B and 6-B) are considerably smaller and less variable (ranging from 0.08 to 0.5). Overall, these results suggest that the trend observed from the combined data set originates in the strings of 18 workers from the pesticide production facility.

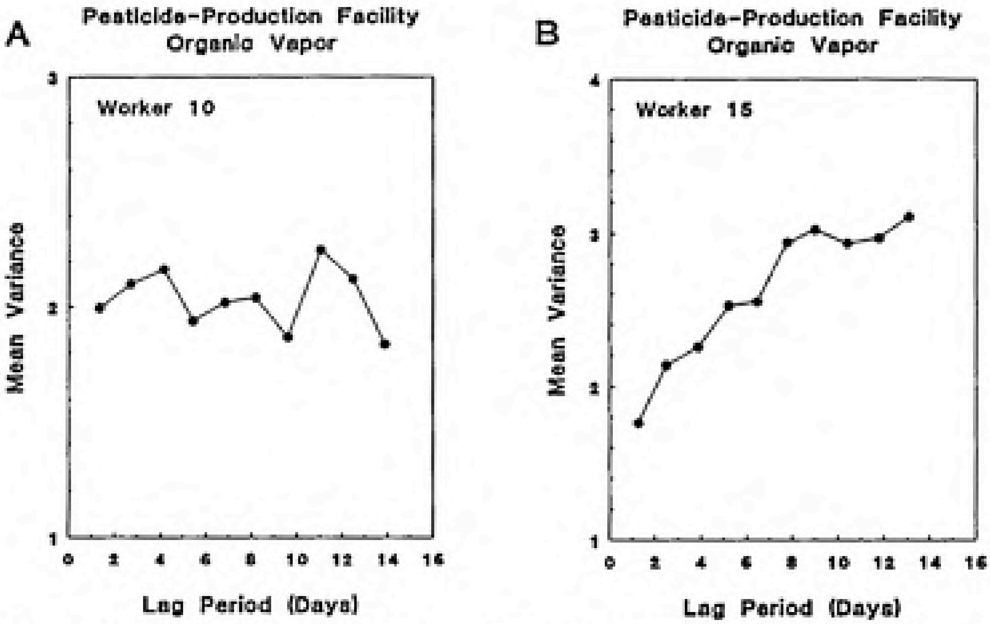

Figure 4. Plots for two workers at the pesticide-production facility. Graph A shows no relationship between variance and lag whereas Graph B depicts an increasing variance with lag. Variances were computed using log-transformed data.

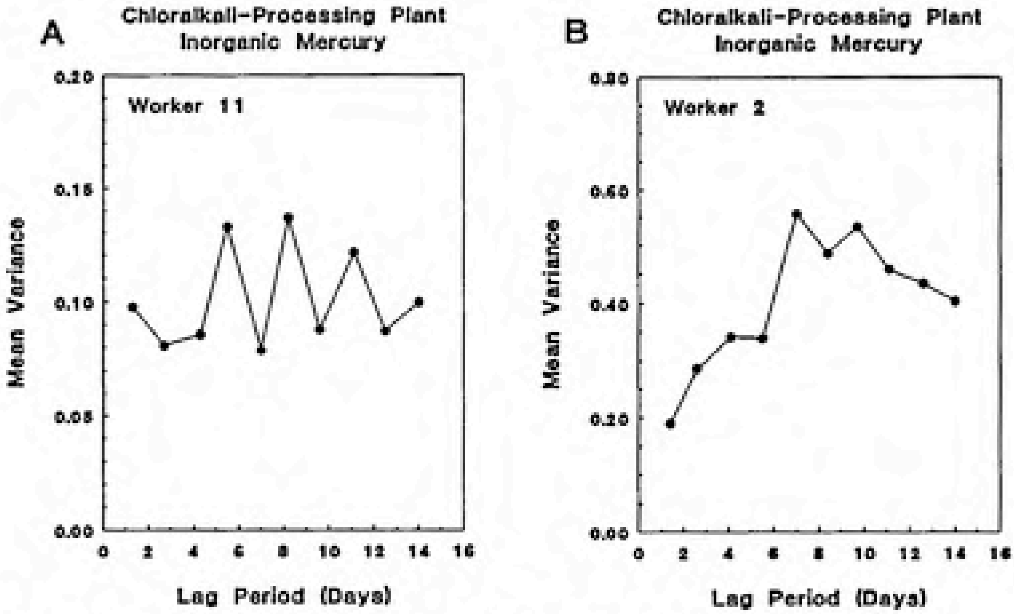

Figure 5. Plots for two workers at the chloralkali-processing plant. Graph A shows no relationship between variance and lag whereas Graph B displays a trend of increasing variance with lag. Variances were computed using log-transformed data.

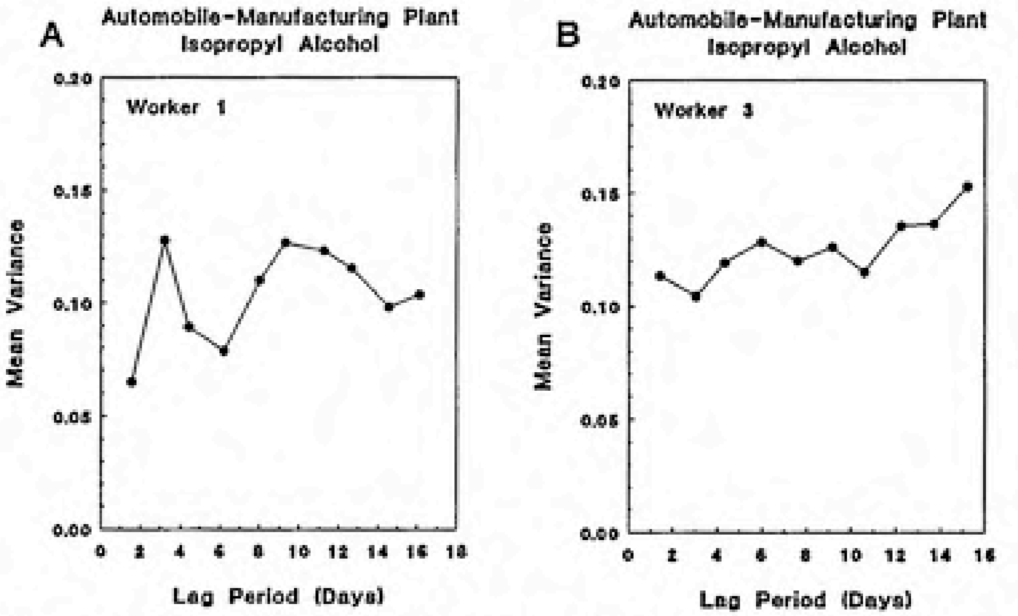

Figure 6. Plots for two workers at the automobile-manufacturing plant. Graph A shows no relationship between variance and lag whereas Graph B displays a trend of increasing variance with lag. Variances were computed using log-transformed data.

Since some workers were sampled over longer intervals and contributed multiple strings of data, the final analysis was conducted by individual time series to decipher differences over time. Forty-five of the time series showed an increase of variance with lag. The majority (42) were drawn from the data collected at the pesticide-production facility with the remaining series split between two workers at the chloralkali-processing plant and one worker at the automobile-production plant.

The contrast between the analyses conducted by worker and by time series focused primarily upon the pesticide-production plant where the overall trend arose. Although 64% of the workers displayed an increasing variance with lag, it was found that approximately 2/3 of the data for these workers showed no such trends. Thus, it appears that relatively few time series per worker dominated the analysis. Figure 7 provides an illustration by plotting five time series for Worker 13 from the pesticide facility. Three of the time series, graphs A-C, show no consistent trend between variance and lag. In contrast, graphs D and E are characterized by marked upward trends, particularly in graph D. The plot for Worker 13 combining all of the time series, in graph F, also shows a trend of increasing variance with lag.

The unevenness in the spacing of the data due to absences and days of non-exposure was assessed by averaging the number of days separating pairs of measurements for each lag period. The data are tabulated for each analysis and appear in Appendix A. Figure 8 plots the relationship between lag and the mean number of days for the analysis of the entire data base. For lags 1 and 10, the mean was approximately 1.4 and 14.2 days, respectively (averaging values for 2,980 pairs of measurements/per lag). Differences between the mean value and lag are relatively small suggesting that missing data did not present significant problems. The comparisons were similar for the other analyses (see Appendix A).

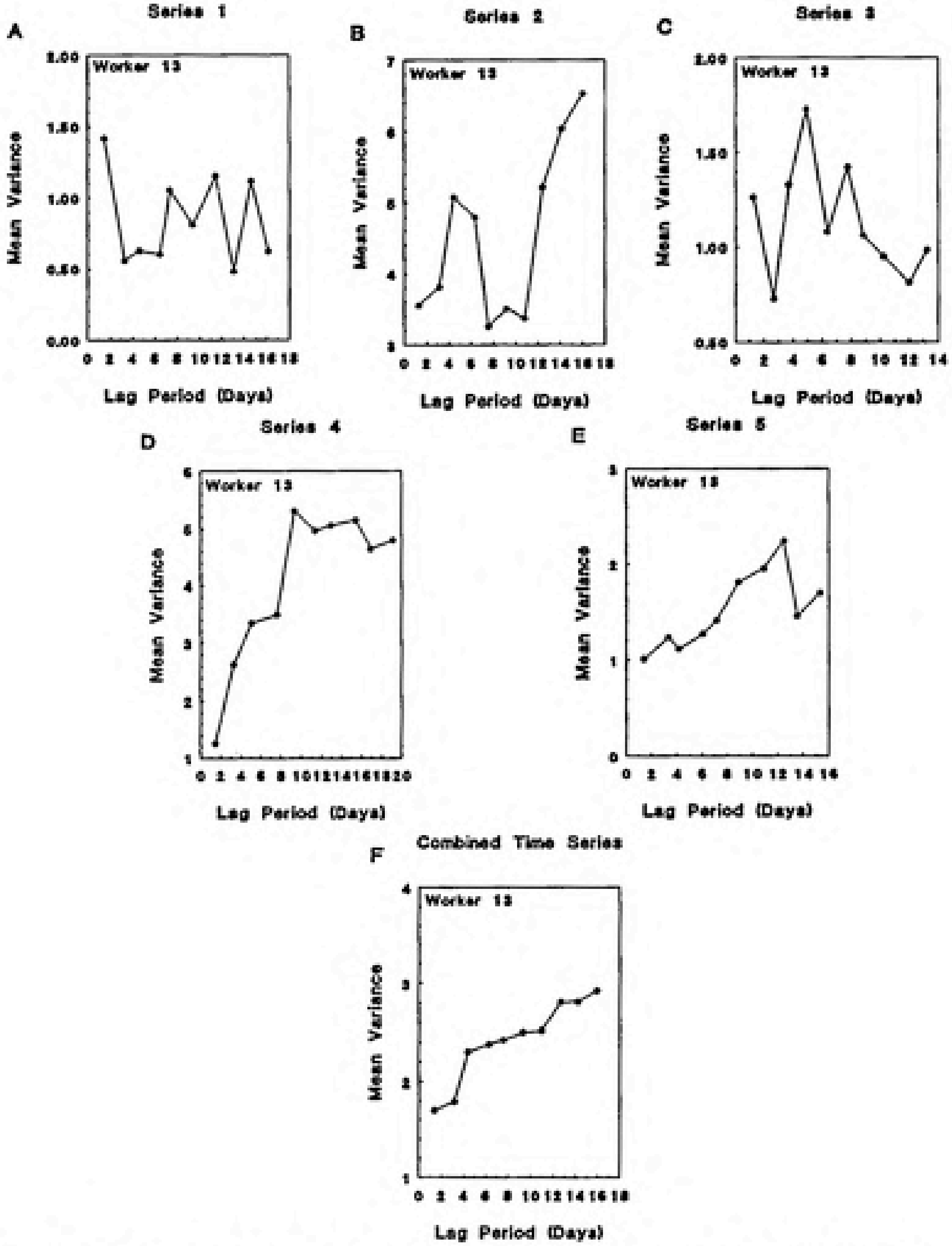

Figure 7. Graphs A–D display five separate time series for Worker 13 at the pesticide plant. Graph F plots the combined data. Variances were computed using log-transformed data.

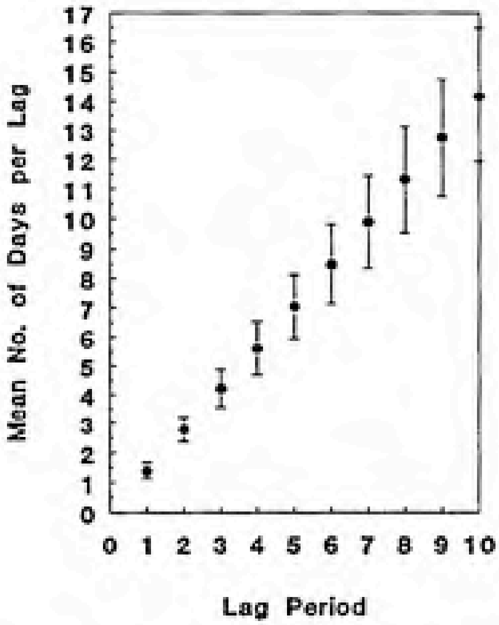

Figure 8. Plot of mean number of days between pairs of measurements vs. lag for all of the data (2,980 pairs of measurements were averaged per lag). Error bars reflect ± 1 standard deviation (SD) from the mean.

Analysis of Stationarity and Autocorrelation

The stationarity and autocorrelation analyses for all 149 time series are tabulated in Appendix B, along with the results from the foregoing analysis evaluating variance and lag. This section is intended to summarize results from these analyses and to present major findings. Particular time series have been selected as examples to highlight differences in stationary behavior and autocorrelated sequences but represent only a fraction of the total number reviewed in the study.

Thirty-four time series appeared to be non-stationary when visually examined. Thirty-eight series had significant first-order autocorrelation coefficients. Both the qualitative assessment for stationarity and the autocorrelation analysis were used to identify time series that appeared to exhibit non-stationary behavior. The time plots for two workers from the pesticide production facility, along with their correlograms, appear in Figure 9. Both the plots and correlograms provide evidence of non-stationarity. The time plot for Worker 26 reveals that the logarithms of exposure initially range between -7.4 to -4, are followed by a string of values below the detection limit and then shift upwards fluctuating between -5 and -.1. The plot for Worker #27 shows a slightly different pattern. The logarithms of exposure remain relatively constant, drop to non-detectable levels and then rise to their highest values. Note that the autocorrelation functions decay slowly to zero providing additional evidence of non-stationarity. The correlograms need to be interpreted carefully, however, because of the string of values in both plots below the detection limit.

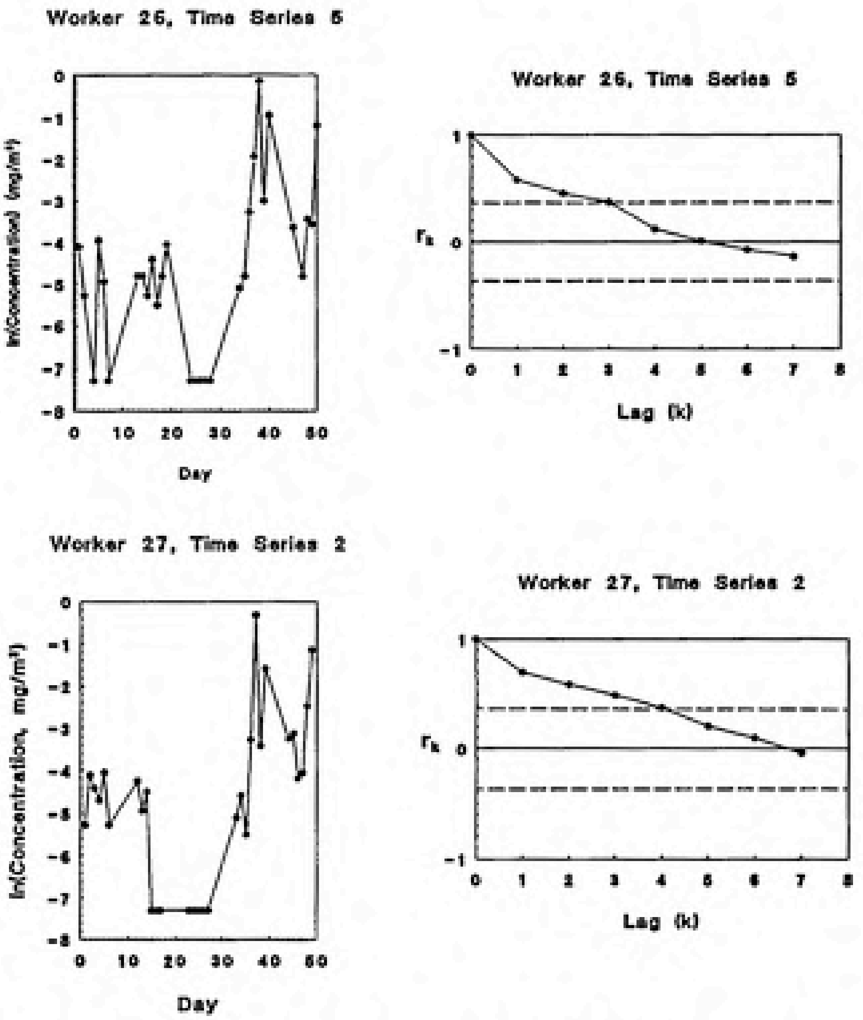

Figure 9. Time plots for two workers at the pesticide facility appear on the left. The dashed lines on the correlograms represent the approximate 95% confidence limits. The autocorrelation functions decay slowly suggesting non-stationary behavior.

To contrast the trend in exposure seen in Figure 9, the time plot and correlogram for a worker exposed to alkyl lead at the lead-manufacturing plant are shown in Figure 10. The plot of air concentrations over time shows no upward or downward movement suggesting a constant mean over the period sampled. There also appears to be relatively little change in the variance. The autocorrelation function behaves quite differently from the correlograms plotted in Figure 9, with none of the autocorrelation coefficients significantly different from zero.

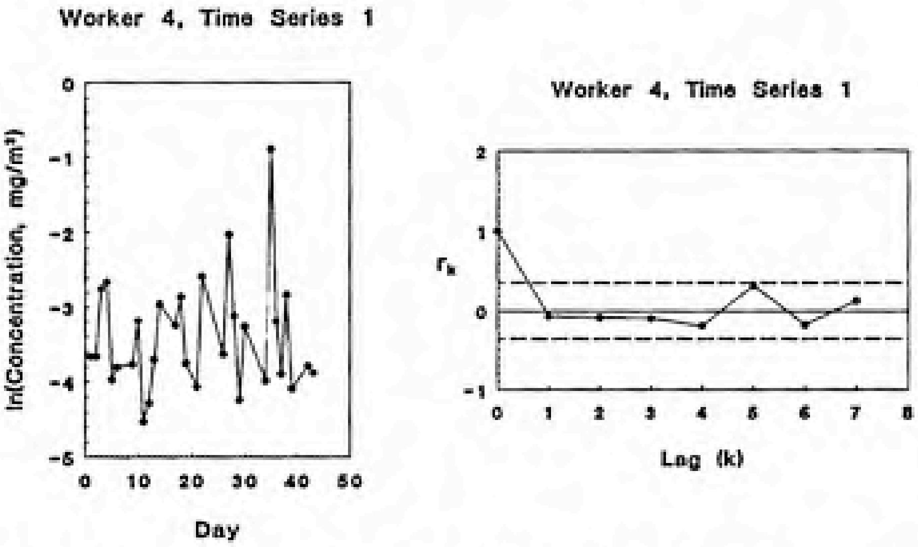

Figure 10. The time plot and correlogram for a worker exposed to alkyl lead at the lead-manufacturing plant. Both graphs indicate stationary behavior. Dashed lines on the correlogram represent the approximate 95% confidence limits.

The Dickey-Fuller test identified 14 time series as non-stationary at the 95% confidence level. These series all came from the pesticide-production facility with the exception of one drawn from the automobile-manufacturing plant. The statistical test identified fewer time series as non-stationary than the method of visually inspecting the time plots (14 vs. 34, respectively). Overall, there was 83% agreement between the formal test and the method of visual inspection. Eleven out of the 14 series (79%) identified as non-stationary by the statistical test were similarly detected by examination of their time plots. None of the longer strings from the pesticide-production facility, ranging between 61 and 140 measurements per string, were non-stationary by the formal test, although 36% (12 out of 33 plots) were non-stationary by visual inspection.

Non-stationary series as assessed formally were transformed by differencing and re-tested. All of the differenced series exhibited stationary behavior by the formal test; one time series was identified as non-stationary by visual examination.

When the stationary series were examined for autocorrelation, 29 significant first-order autocorrelation coefficients were detected. However, most of these (25) were barely significant. Only four coefficients were larger than 0.5; all of these came from the pesticide-production facility. Figure 11 shows the time plot and correlogram for a series generating the highest coefficient (0.612). It can be seen from the time plot that consecutive values are likely to be on the same side of the mean (average value is -5.38). Twenty-six time series had significant coefficients at lags greater than one. The physical significance of these coefficients is difficult to interpret and will not be considered further.

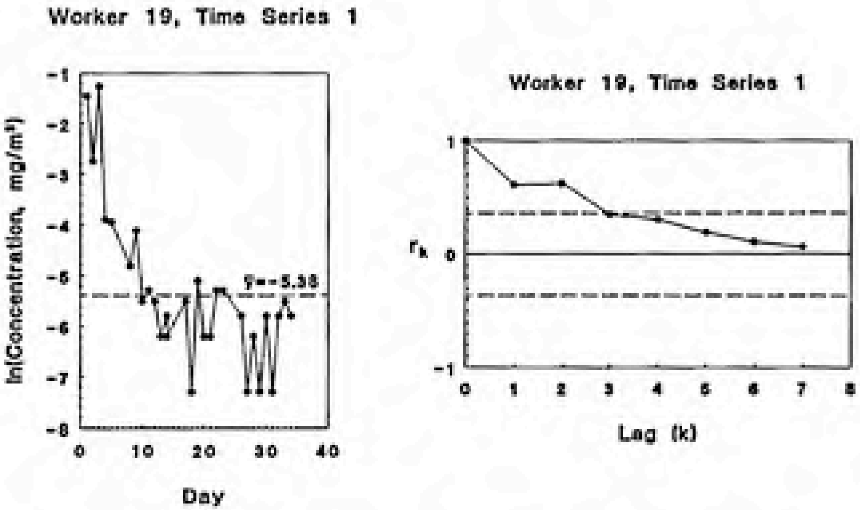

Figure 11. The time plot and correlogram for a worker exposed to an organic vapor at the pesticide-production facility. The dashed lines on the correlogram represent the approximate 95% confidence limits.

Ten of the 14 non-stationary time series identified from the formal test showed no autocorrelation after differencing. The differenced series producing significant results all had first-order correlation coefficients that were negative and relatively large, contributing three out of the four highest values. The significance of these coefficients requires careful interpretation. If a time series consists purely of a trend and a stationary random component, then taking first differences will remove the trend and result in a series whose sample autocorrelation function rapidly falls to zero (Gottman, 1981). Figure 12 illustrates an example. The time plot for Worker 2 at the automobile-manufacturing plant appears to linearly increase over time. The initial autocorrelation analysis yielded significant serial coefficients for lags one through three (0.654, 0.485, 0.420, respectively) but this analysis is not valid if the underlying process is non-stationary. The plot of first differences appears stationary (Figure 12-B); the autocorrelation analysis on the differenced series produced no significant correlation coefficients.

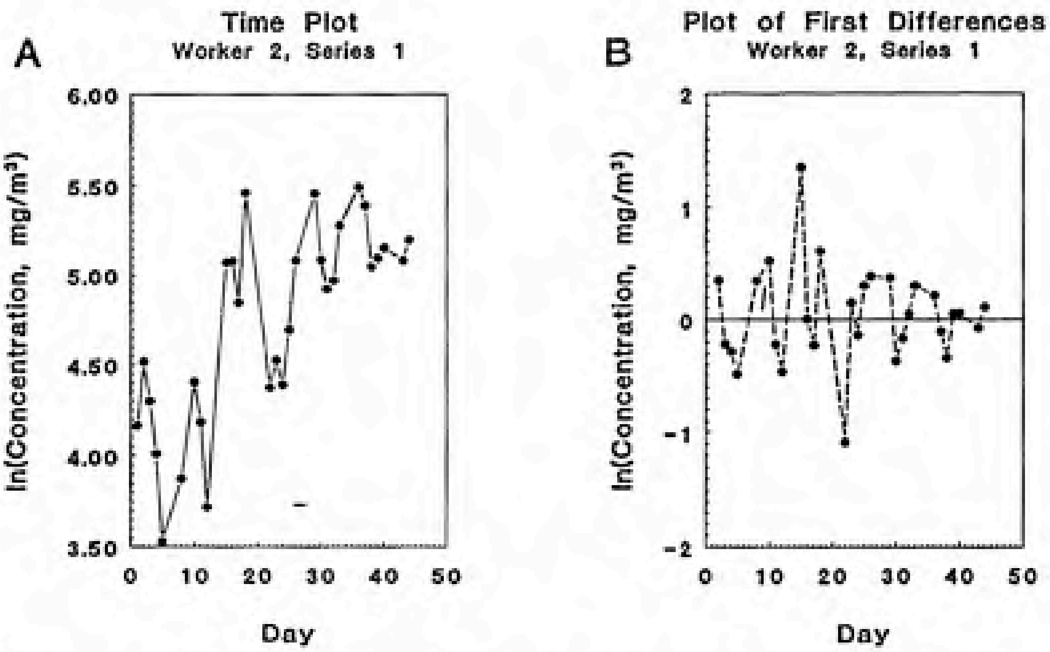

Figure 12. Time plot for a worker at the automobile plant shows a linear increase over time. Taking first differences removes non-stationarity as evidenced by plot B.

In some instances, first differencing may not be an appropriate remedy for non-stationarity if the series does not appear to increase linearly over time. To illustrate this point, Figure 13 shows the time series for Worker 9 at the pesticide-production facility that was assessed as non-stationary by both the formal test and visual inspection. Here no linear trend is evident (although there appears to be some cycling) and the variance is not constant over time. Thus, the significant autocorrelation coefficient obtained from the differenced data is suspect and may not be interpretable.

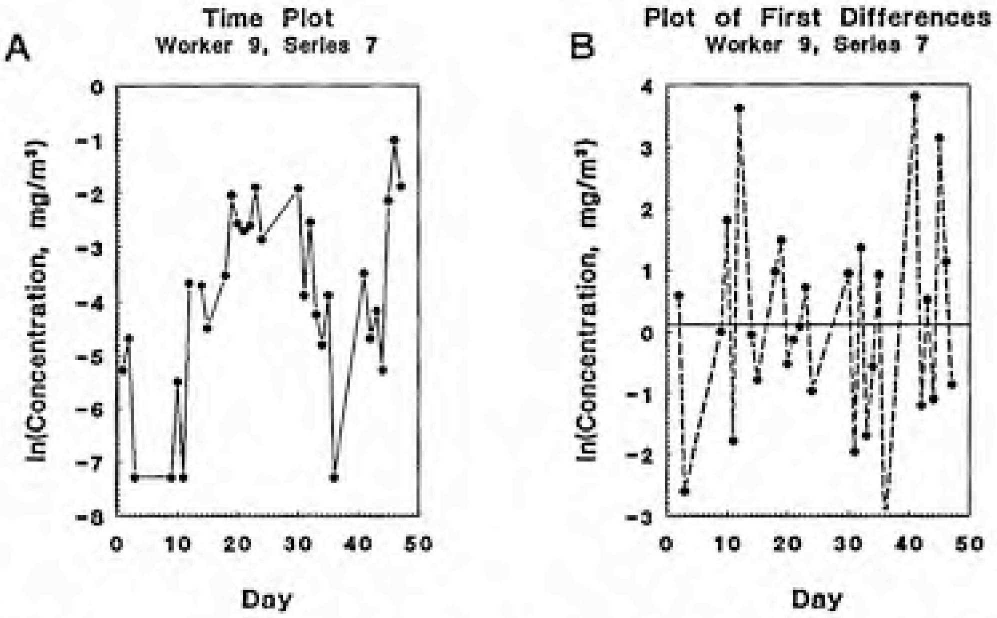

Figure 13. Non-stationary time plot for a worker at the pesticide plant that appears to cycle over time. Taking first differences may not be appropriate as a means to remove non-stationarity.

To determine the extent to which autocorrelation or non-stationarity may explain the trend between variance and lag among pairs of measurements separated by different intervals, the results from these two analyses were coupled with the 45 time series displaying an increasing variance with lag and appear in Table 3. Thirteen time series (29%) were non-stationary according to the Dickey-Fuller test while twenty series (44%) were flagged non-stationary by visual inspection. Nineteen stationary series (assessed by the formal test) had significant first-order autocorrelation coefficients, including four negative coefficients obtained from the differenced series. Together non-stationarity and autocorrelation explain the trend between variance and lag for 60% of the series.

Table 3. Results from the stationarity test and autocorrelation analysis for time series where the variance increased along with the interval between measurements.

Data Set	Worker	Time Series	Test for Stationarity*	1st-Order Autocorrelation Coefficient
Pesticide-Manufacturing Plant	1	3	NS (NS)	-0.537+
		7	NS (NS)	-0.409+
	6	3	NS (NS)	-
	9	7	NS (NS)	-0.510+
		8	NS (S)	
	13	4	NS (S)	-
	15	4	NS (NS)	-
		11	NS (NS)	-
	24	1	NS (S)	-
	26	2	NS (NS)	-0.571+
		5	NS (NS)	-
	27	2	NS (NS)	-
Automobile-Manufacturing Plant	2	1	NS (NS)	-

*NS=Non-stationary; S=Stationary as assessed formally; values in parentheses are results from visual inspection of the time plots.

+Autocorrelation performed on differenced series if assessed non-stationary by the formal test; values in parentheses are results following differencing based on visual inspection of plots.

Table 3 (Continued)

Data Set	Worker	Time Series	Test for Stationarity*	1st-Order Autocorrelation Coefficient
Pesticide-Manufacturing Plant	6	1	S (NS)	0.397 (-0.474)+
		7	S (S)	0.457
	11	3	S (NS)	0.386 (-0.433)+
	15	1	S (S)	0.391
		3	S (S)	0.406
		13	S (S)	0.382
	17	2	S (NS)	0.495 (-0.676)+
	19	1	S (NS)	0.612 (-0.612)+
	26	6	S (NS)	0.367 (-0.451)+
	27	1	S (S)	0.451
		5	S (NS)	0.424 (-)+
	28	2	S (S)	0.438
		4	S (NS)	0.428 (-0.454)+
Chloralkali-Manufacturing Plant	2	1	S (S)	0.362
Pesticide-Manufacturing Plant	1	1	S (NS)	(-0.389)
		6	S (S)	-
	6	5	S (S)	-
		6	S (S)	-
	7	7	S (S)	-
		9	S (S)	-
	11	1	S (NS)	(-0.464)
		4	S (NS)	(-0.426)
	12	2	S (S)	-
	13	5	S (S)	-
	14	1	S (S)	-
	15	5	S (S)	-
		10	S (S)	-
	21	1	S (S)	-
	23	4	S (S)	-
	25	1	S (S)	-
	26	4	S (S)	-
	26	4	S (S)	-
Chloralkali-Manufacturing Plant	10	1	S (S)	-

*NS = Non-stationary; S = Stationary as assessed formally; values in parentheses are results from visual inspection of the time plots.

+Autocorrelation performed on differenced series if assessed non-stationary by the formal test; values in parentheses are results following differencing based on visual inspection of plots.

CONCLUSIONS

Proper assessment of exposure requires that the variability in air concentration levels be taken into account. Specification of the variance is generally considered in the context of a statistical distribution of the underlying population of exposures. Such a distribution may be incorrectly specified, however, if day-to-day exposures are autocorrelated and this correlation is not statistically assessed. Indeed significant errors in the estimated parameters can arise from campaigns of a few days time (Francis et al., 1989; Buringh and Lanting, 1991). Time-series analysis affords methods to assess autocorrelation and to build a temporal component into the model describing exposures but requires relatively long strings of consecutive measurements that are rarely collected in practice.

Given the lack of suitable data, indirect methods may provide useful alternatives to traditional time-series analysis (Buringh and Lanting, 1991). Specifically, a statistical property regarding the variance has been used. Since positively autocorrelated data measured during brief intervals will underestimate the variability, differences between estimates of the variances between data collected over brief intervals compared to longer time periods may provide some evidence of autocorrelation.

This analysis suggests that the validity of this indirect method depends upon careful control of factors likely to contribute to variability, including industry, location, type of exposure, and worker. The results confirm the observation of Buringh and Lanting (1991) that the variance tends to increase with the interval between measurements. However, by controlling for the above confounding factors, this analysis provided an additional opportunity to isolate the effect by data set, worker, and time series. Isolation by data set showed that the trend was restricted to only one of the five data sets available for investigation. Dissecting the data by worker and then by individual time series further revealed that the trend was due to the influence of less than one-third of the time series.

The data set responsible for the observed trend was the largest both in terms of the number of workers sampled and the number of time series contributing to the analysis. Besides dominating by size, the data set was characterized by variances which were much larger than those of the other sets. Thus, few time series containing the trends 'contaminated' the larger data base (Figure 1) suggesting a more general problem. It is possible that a data set with similar characteristics unduly influenced the analysis conducted by Buringh and Lanting (1991).

Focusing now on the time series where the variance increased with lag, autocorrelation and non-stationarity appear to have contributed to 60% of the trends. The significant first-order autocorrelation coefficients range between 0.362 and 0.612. Some of these coefficients are small and may have only contributed marginally to the observed trend. It is important to note, however, that over half of the significant coefficients from the entire analysis were restricted to the series where the variance increased with lag.

Finally, visual inspection of the plots for non-stationarity in the mean or variance appears to be fairly robust when compared to the statistical test. The ad hoc method may in fact be preferable since no underlying model is assumed and it is not constrained by small sample sizes, which can severely limit the power of formal testing procedures. The percentage breakdown of the stationarity analysis for the entire data set and for the various subsets of data appears in Figure 14.

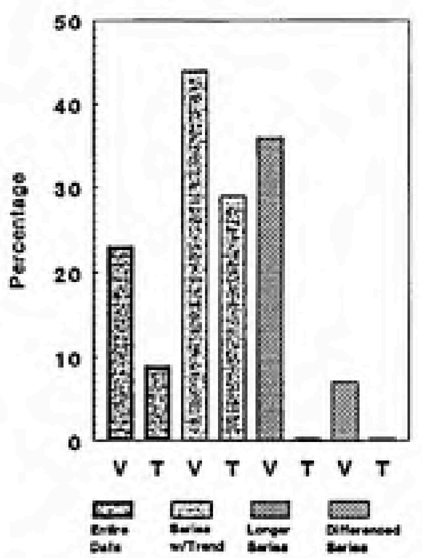

Figure 14. Percentage breakdown of non-stationarity between the formal test (T) and visual inspection (V).

The issue of stationarity needs to be examined in greater detail. However, if our results are typical of other workplaces, sampling strategies may not need to address problems associated with autocorrelation or non-stationarity.

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APPENDIX A

Breakdown of the Interval Between Pairs of Measurements

Appendix A

BREAKDOWN FOR ALL OF THE DATA						
N Obs	Variable	Minimum	Maximum	Mean	Std Dev	
149	MEAND1	0.8	2.35	1.387584	0.252816	
149	MEAND2	1.8	4.4	2.786242	0.422943	
149	MEAND3	2.5	5.9	4.215436	0.655458	
149	MEAND4	3.3	8.45	5.613758	0.915332	
149	MEAND5	4.2	9.95	7.043624	1.083776	
149	MEAND6	4.85	11.8	8.477517	1.333982	
149	MEAND7	5.75	14.15	9.891275	1.548678	
149	MEAND8	6.55	16.35	11.31745	1.780676	
149	MEAND9	7.35	18.45	12.74564	2.013442	
149	MEAND10	8.15	21.1	14.18356	2.268173	
BREAKDOWN BY DATA SET						
Alkyl Lead Manufacturing Plant (Alkyl Lead)						
N Obs	Variable	Minimum	Maximum	Mean	Std Dev	
4	MEAND1	1.15	1.55	1.375	0.184842	
4	MEAND2	2.5	2.9	2.7875	0.193111	
4	MEAND3	3.8	4.4	4.1	0.258199	
4	MEAND4	5.1	5.8	5.4625	0.303795	
4	MEAND5	6.7	7.25	6.9625	0.256174	
4	MEAND6	8	8.8	8.4625	0.363719	
4	MEAND7	9.2	10.3	9.85	0.479583	
4	MEAND8	10.5	11.7	11.25	0.544671	
4	MEAND9	11.8	13.1	12.625	0.618466	
4	MEAND10	13.2	14.6	14.075	0.670199	
Alkyl Lead Manufacturing Plant (Inorganic Lead)						
N Obs	Variable	Minimum	Maximum	Mean	Std Dev	
4	MEAND1	1.3	1.6	1.3875	0.143614	
4	MEAND2	2.5	2.9	2.65	0.173205	
4	MEAND3	3.9	4.45	4.1625	0.256174	
4	MEAND4	5.1	5.7	5.375	0.25	
4	MEAND5	6.5	7.2	6.875	0.377492	
4	MEAND6	8	8.6	8.275	0.320156	
4	MEAND7	9.3	10.2	9.6875	0.458939	
4	MEAND8	10.6	11.8	11.1625	0.652399	
4	MEAND9	11.8	13.2	12.525	0.780491	
4	MEAND10	13.2	14.6	13.9	0.60829	

Pesticide-Manufacturing Plant						
N Obs	Variable	Minimum	Maximum	Mean	Std Dev	
120	MEAND1	0.8	2.35	1.382083	0.274382	
120	MEAND2	1.8	4.4	2.779167	0.455433	
120	MEAND3	2.5	5.9	4.1975	0.715872	
120	MEAND4	3.3	8.45	5.593333	1.000881	
120	MEAND5	4.2	9.95	7.003333	1.185694	
120	MEAND6	4.85	11.8	8.428333	1.452262	
120	MEAND7	5.75	14.15	9.834167	1.683184	
120	MEAND8	6.55	16.35	11.25792	1.942374	
120	MEAND9	7.35	18.45	12.67875	2.198574	
120	MEAND10	8.15	21.1	14.10833	2.484011	
Chloralkali-Processing Plant						
N Obs	Variable	Minimum	Maximum	Mean	Std Dev	
15	MEAND1	1.2	1.65	1.413333	0.140746	
15	MEAND2	2.5	3.45	2.803333	0.268239	
15	MEAND3	4	5.25	4.31	0.319151	
15	MEAND4	5.4	6.8	5.71	0.414987	
15	MEAND5	7	8.55	7.223333	0.466701	
15	MEAND6	8.2	10.75	8.663333	0.742454	
15	MEAND7	9.6	12.45	10.11	0.871616	
15	MEAND8	11	13.7	11.51333	0.89092	
15	MEAND9	12.5	15.4	12.97	0.933082	
15	MEAND10	14	16.8	14.44333	0.924057	
Automobile-Manufacturing Plant						
N Obs	Variable	Minimum	Maximum	Mean	Std Dev	
6	MEAND1	1.35	1.55	1.441667	0.073598	
6	MEAND2	2.6	3.25	2.975	0.238223	
6	MEAND3	4.2	4.8	4.45	0.204939	
6	MEAND4	5.65	6.3	6.041667	0.247824	
6	MEAND5	7.25	8	7.566667	0.284019	
6	MEAND6	8.8	9.45	9.141667	0.26347	
6	MEAND7	10.05	11.25	10.65	0.475395	
6	MEAND8	11.55	13	12.16667	0.564506	
6	MEAND9	13	14.55	13.75	0.634035	
6	MEAND10	14.45	16.1	15.3	0.683374	

DATA SET AND WORKER						
Alkyl Lead Manufacturing Plant (Alkyl Lead)						
Worker=1						
N Obs	Variable	Minimum	Maximum	Mean	Std Dev	
1	MEAND1	1.15	1.15	1.15	.	
1	MEAND2	2.85	2.85	2.85	.	
1	MEAND3	4	4	4	.	
1	MEAND4	5.35	5.35	5.35	.	
1	MEAND5	6.8	6.8	6.8	.	
1	MEAND6	8.35	8.35	8.35	.	
1	MEAND7	9.8	9.8	9.8	.	
1	MEAND8	11.2	11.2	11.2	.	
1	MEAND9	12.5	12.5	12.5	.	
1	MEAND10	13.9	13.9	13.9	.	
Worker=2						
N Obs	Variable	Minimum	Maximum	Mean	Std Dev	
1	MEAND1	1.5	1.5	1.5	.	
1	MEAND2	2.9	2.9	2.9	.	
1	MEAND3	4.4	4.4	4.4	.	
1	MEAND4	5.6	5.6	5.6	.	
1	MEAND5	7.1	7.1	7.1	.	
1	MEAND6	8.8	8.8	8.8	.	
1	MEAND7	10.1	10.1	10.1	.	
1	MEAND8	11.6	11.6	11.6	.	
1	MEAND9	13.1	13.1	13.1	.	
1	MEAND10	14.6	14.6	14.6	.	
Worker=3						
N Obs	Variable	Minimum	Maximum	Mean	Std Dev	
1	MEAND1	1.3	1.3	1.3	.	
1	MEAND2	2.5	2.5	2.5	.	
1	MEAND3	3.8	3.8	3.8	.	
1	MEAND4	5.1	5.1	5.1	.	
1	MEAND5	6.7	6.7	6.7	.	
1	MEAND6	8	8	8	.	
1	MEAND7	9.2	9.2	9.2	.	
1	MEAND8	10.5	10.5	10.5	.	
1	MEAND9	11.8	11.8	11.8	.	

1	MEAND10	13.2	13.2	13.2	.	
Worker=4						
N Obs	Variable	Minimum	Maximum	Mean	Std Dev	
1	MEAND1	1.55	1.55	1.55	.	
1	MEAND2	2.9	2.9	2.9	.	
1	MEAND3	4.2	4.2	4.2	.	
1	MEAND4	5.8	5.8	5.8	.	
1	MEAND5	7.25	7.25	7.25	.	
1	MEAND6	8.7	8.7	8.7	.	
1	MEAND7	10.3	10.3	10.3	.	
1	MEAND8	11.7	11.7	11.7	.	
1	MEAND9	13.1	13.1	13.1	.	
1	MEAND10	14.6	14.6	14.6	.	
Alkyl Lead Manufacturing Plant (Inorganic Lead)						
Worker=1						
N Obs	Variable	Minimum	Maximum	Mean	Std Dev	
1	MEAND1	1.3	1.3	1.3	.	
1	MEAND2	2.6	2.6	2.6	.	
1	MEAND3	4	4	4	.	
1	MEAND4	5.3	5.3	5.3	.	
1	MEAND5	6.6	6.6	6.6	.	
1	MEAND6	8	8	8	.	
1	MEAND7	9.3	9.3	9.3	.	
1	MEAND8	10.6	10.6	10.6	.	
1	MEAND9	11.8	11.8	11.8	.	
1	MEAND10	13.2	13.2	13.2	.	
Worker=2						
N Obs	Variable	Minimum	Maximum	Mean	Std Dev	
1	MEAND1	1.6	1.6	1.6	.	
1	MEAND2	2.6	2.6	2.6	.	
1	MEAND3	4.3	4.3	4.3	.	
1	MEAND4	5.4	5.4	5.4	.	
1	MEAND5	7.2	7.2	7.2	.	
1	MEAND6	8.5	8.5	8.5	.	
1	MEAND7	10.2	10.2	10.2	.	
1	MEAND8	11.8	11.8	11.8	.	
1	MEAND9	13.2	13.2	13.2	.	

1	MEAND10	14.6	14.6	14.6	.	
Worker=3						
N Obs	Variable	Minimum	Maximum	Mean	Std Dev	
1	MEAND1	1.3	1.3	1.3	.	
1	MEAND2	2.5	2.5	2.5	.	
1	MEAND3	3.9	3.9	3.9	.	
1	MEAND4	5.1	5.1	5.1	.	
1	MEAND5	6.5	6.5	6.5	.	
1	MEAND6	8	8	8	.	
1	MEAND7	9.3	9.3	9.3	.	
1	MEAND8	10.6	10.6	10.6	.	
1	MEAND9	11.9	11.9	11.9	.	
1	MEAND10	13.2	13.2	13.2	.	
Worker=4						
N Obs	Variable	Minimum	Maximum	Mean	Std Dev	
1	MEAND1	1.35	1.35	1.35	.	
1	MEAND2	2.9	2.9	2.9	.	
1	MEAND3	4.45	4.45	4.45	.	
1	MEAND4	5.7	5.7	5.7	.	
1	MEAND5	7.2	7.2	7.2	.	
1	MEAND6	8.6	8.6	8.6	.	
1	MEAND7	9.95	9.95	9.95	.	
1	MEAND8	11.65	11.65	11.65	.	
1	MEAND9	13.2	13.2	13.2	.	
1	MEAND10	14.6	14.6	14.6	.	
Pesticide-Manufacturing Plant						
Worker=1						
N Obs	Variable	Minimum	Maximum	Mean	Std Dev	
8	MEAND1	1.1	1.8	1.43125	0.261776	
8	MEAND2	2.3	3.35	2.775	0.364496	
8	MEAND3	3.45	5.15	4.225	0.597614	
8	MEAND4	4.35	7.3	5.55	0.957676	
8	MEAND5	5.4	8.55	7.025	1.058975	
8	MEAND6	6.55	10.5	8.34375	1.239366	
8	MEAND7	7.75	12.2	9.79375	1.479729	
8	MEAND8	8.75	13.85	11.175	1.694107	
8	MEAND9	9.85	15.35	12.5375	1.851592	

8	MEAND10	10.9	17.05	13.9125	2.086307	
Worker=2						
N Obs	Variable	Minimum	Maximum	Mean	Std Dev	
1	MEAND1	1.3	1.3	1.3	.	
1	MEAND2	2.9	2.9	2.9	.	
1	MEAND3	4.3	4.3	4.3	.	
1	MEAND4	5.6	5.6	5.6	.	
1	MEAND5	7.1	7.1	7.1	.	
1	MEAND6	8.6	8.6	8.6	.	
1	MEAND7	10.3	10.3	10.3	.	
1	MEAND8	11.6	11.6	11.6	.	
1	MEAND9	13.1	13.1	13.1	.	
1	MEAND10	14.5	14.5	14.5	.	
Worker=3						
N Obs	Variable	Minimum	Maximum	Mean	Std Dev	
1	MEAND1	1.6	1.6	1.6	.	
1	MEAND2	3.1	3.1	3.1	.	
1	MEAND3	4.65	4.65	4.65	.	
1	MEAND4	5.75	5.75	5.75	.	
1	MEAND5	7.25	7.25	7.25	.	
1	MEAND6	9	9	9	.	
1	MEAND7	10.4	10.4	10.4	.	
1	MEAND8	11.65	11.65	11.65	.	
1	MEAND9	13.05	13.05	13.05	.	
1	MEAND10	14.45	14.45	14.45	.	
Worker=4						
N Obs	Variable	Minimum	Maximum	Mean	Std Dev	
1	MEAND1	2.1	2.1	2.1	.	
1	MEAND2	3.6	3.6	3.6	.	
1	MEAND3	5.2	5.2	5.2	.	
1	MEAND4	6.85	6.85	6.85	.	
1	MEAND5	9.15	9.15	9.15	.	
1	MEAND6	10.85	10.85	10.85	.	
1	MEAND7	12.2	12.2	12.2	.	
1	MEAND8	14.4	14.4	14.4	.	
1	MEAND9	16.1	16.1	16.1	.	
1	MEAND10	17.9	17.9	17.9	.	

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Worker=5						
N Obs	Variable	Minimum	Maximum	Mean	Std Dev	
1	MEAND1	1.4	1.4	1.4	.	
1	MEAND2	3.2	3.2	3.2	.	
1	MEAND3	4.35	4.35	4.35	.	
1	MEAND4	6.1	6.1	6.1	.	
1	MEAND5	7.65	7.65	7.65	.	
1	MEAND6	8.95	8.95	8.95	.	
1	MEAND7	10.45	10.45	10.45	.	
1	MEAND8	12	12	12	.	
1	MEAND9	13.5	13.5	13.5	.	
1	MEAND10	14.9	14.9	14.9	.	
Worker=6						
N Obs	Variable	Minimum	Maximum	Mean	Std Dev	
8	MEAND1	1.05	1.85	1.38125	0.253458	
8	MEAND2	2.2	3.25	2.83125	0.399944	
8	MEAND3	3.1	5	4.26875	0.65024	
8	MEAND4	4.45	6.85	5.68125	0.942617	
8	MEAND5	5.4	8.45	7.0875	1.113473	
8	MEAND6	6.45	10.3	8.68125	1.465785	
8	MEAND7	7.6	11.9	9.975	1.556553	
8	MEAND8	8.6	13.7	11.575	1.87102	
8	MEAND9	10	15.6	12.975	2.008375	
8	MEAND10	11.05	17.25	14.4625	2.265542	
Worker=7						
N Obs	Variable	Minimum	Maximum	Mean	Std Dev	
9	MEAND1	0.8	1.65	1.294444	0.283333	
9	MEAND2	1.8	3.6	2.744444	0.587071	
9	MEAND3	2.65	5.4	4.177778	1.058924	
9	MEAND4	3.4	6.65	5.427778	1.160849	
9	MEAND5	4.2	8.4	6.955556	1.525911	
9	MEAND6	5	10.1	8.377778	1.819875	
9	MEAND7	5.85	11.6	9.644444	2.064195	
9	MEAND8	6.65	13.35	11.01667	2.441055	
9	MEAND9	7.45	15.45	12.41111	2.799417	
9	MEAND10	8.25	17.1	13.85	3.159114	

Worker=8						
N Obs	Variable	Minimum	Maximum	Mean	Std Dev	
1	MEAND1	1.45	1.45	1.45	.	
1	MEAND2	3.1	3.1	3.1	.	
1	MEAND3	4.35	4.35	4.35	.	
1	MEAND4	6.45	6.45	6.45	.	
1	MEAND5	7.7	7.7	7.7	.	
1	MEAND6	9.4	9.4	9.4	.	
1	MEAND7	10.8	10.8	10.8	.	
1	MEAND8	12.7	12.7	12.7	.	
1	MEAND9	14.2	14.2	14.2	.	
1	MEAND10	15.7	15.7	15.7	.	
Worker=9						
N Obs	Variable	Minimum	Maximum	Mean	Std Dev	
8	MEAND1	1.1	1.45	1.24375	0.126597	
8	MEAND2	2.2	3.4	2.7875	0.39438	
8	MEAND3	3.25	4.8	4.0875	0.562996	
8	MEAND4	4.1	6.65	5.5	0.893628	
8	MEAND5	5.15	8	6.91875	0.977584	
8	MEAND6	6.2	9.7	8.20625	1.208729	
8	MEAND7	6.95	11.2	9.6125	1.579048	
8	MEAND8	7.85	13.05	10.9375	1.7908	
8	MEAND9	9	14.25	12.25625	1.916924	
8	MEAND10	9.9	15.9	13.59375	2.202667	
Worker=10						
N Obs	Variable	Minimum	Maximum	Mean	Std Dev	
10	MEAND1	1	1.9	1.36	0.28655	
10	MEAND2	1.95	3.3	2.72	0.475044	
10	MEAND3	3	4.9	4.17	0.704825	
10	MEAND4	3.95	7.45	5.435	0.952788	
10	MEAND5	5.05	8.3	6.85	1.074709	
10	MEAND6	5.85	10.35	8.185	1.382841	
10	MEAND7	6.9	12.05	9.61	1.656268	
10	MEAND8	7.8	13.3	11.05	1.873055	
10	MEAND9	8.65	15.4	12.475	2.188892	
10	MEAND10	9.65	17.05	13.885	2.491658	

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Worker=11						
N Obs	Variable	Minimum	Maximum	Mean	Std Dev	
6	MEAND1	1.1	2	1.358333	0.341199	
6	MEAND2	2.1	3.1	2.783333	0.360093	
6	MEAND3	3.2	5.55	4.158333	0.818179	
6	MEAND4	4.3	7.85	5.691667	1.176187	
6	MEAND5	5.4	8.75	6.9	1.090871	
6	MEAND6	6.3	11.2	8.508333	1.595436	
6	MEAND7	7.7	12.85	9.95	1.728873	
6	MEAND8	8.6	14.75	11.3	2.036418	
6	MEAND9	9.7	16.75	12.65	2.31862	
6	MEAND10	10.7	18.25	13.99167	2.449371	
Worker=12						
N Obs	Variable	Minimum	Maximum	Mean	Std Dev	
2	MEAND1	1.55	1.6	1.575	0.035355	
2	MEAND2	2.75	3.1	2.925	0.247487	
2	MEAND3	4.9	4.95	4.925	0.035355	
2	MEAND4	6.35	6.8	6.575	0.318198	
2	MEAND5	7.5	7.7	7.6	0.141421	
2	MEAND6	8.75	9.25	9	0.353553	
2	MEAND7	10.4	10.75	10.575	0.247487	
2	MEAND8	11.75	12.55	12.15	0.565685	
2	MEAND9	13.35	13.8	13.575	0.318198	
2	MEAND10	14.85	15.4	15.125	0.388909	
Worker=13						
N Obs	Variable	Minimum	Maximum	Mean	Std Dev	
5	MEAND1	1.25	1.5	1.38	0.103682	
5	MEAND2	2.65	3.35	3.15	0.289396	
5	MEAND3	3.7	5.1	4.41	0.52607	
5	MEAND4	4.9	7.6	6.27	0.966049	
5	MEAND5	6.35	9.35	7.55	1.104536	
5	MEAND6	7.75	11.4	9.32	1.321268	
5	MEAND7	8.85	12.95	10.98	1.469098	
5	MEAND8	10.25	15.45	12.73	1.858292	
5	MEAND9	12	16.95	14.24	1.801874	
5	MEAND10	13.25	19.15	15.98	2.117074	

Worker=14						
N Obs	Variable	Minimum	Maximum	Mean	Std Dev	
1	MEAND1	1.6	1.6	1.6	.	
1	MEAND2	3.1	3.1	3.1	.	
1	MEAND3	4.5	4.5	4.5	.	
1	MEAND4	6.05	6.05	6.05	.	
1	MEAND5	7.9	7.9	7.9	.	
1	MEAND6	9.2	9.2	9.2	.	
1	MEAND7	11.3	11.3	11.3	.	
1	MEAND8	12.25	12.25	12.25	.	
1	MEAND9	14	14	14	.	
1	MEAND10	15.65	15.65	15.65	.	
Worker=15						
N Obs	Variable	Minimum	Maximum	Mean	Std Dev	
14	MEAND1	0.95	1.65	1.25	0.257951	
14	MEAND2	1.85	3.4	2.485714	0.445244	
14	MEAND3	2.5	5.35	3.882143	0.83565	
14	MEAND4	3.3	7.15	5.2	1.168826	
14	MEAND5	4.25	8.85	6.442857	1.318632	
14	MEAND6	4.85	10.25	7.785714	1.651623	
14	MEAND7	5.75	12.7	8.982143	1.871508	
14	MEAND8	6.55	14.2	10.39643	2.225073	
14	MEAND9	7.35	16.25	11.76429	2.574911	
14	MEAND10	8.15	18.2	13.07857	2.968794	
Worker=16						
N Obs	Variable	Minimum	Maximum	Mean	Std Dev	
1	MEAND1	1.2	1.2	1.2	.	
1	MEAND2	2.5	2.5	2.5	.	
1	MEAND3	3.75	3.75	3.75	.	
1	MEAND4	4.9	4.9	4.9	.	
1	MEAND5	5.95	5.95	5.95	.	
1	MEAND6	7.05	7.05	7.05	.	
1	MEAND7	8.2	8.2	8.2	.	
1	MEAND8	9.35	9.35	9.35	.	
1	MEAND9	10.45	10.45	10.45	.	
1	MEAND10	11.6	11.6	11.6	.	

Worker=17					
N Obs	Variable	Minimum	Maximum	Mean	Std Dev
4	MEAND1	1.1	1.7	1.2625	0.292618
4	MEAND2	2.3	2.9	2.45	0.3
4	MEAND3	3.45	5.1	3.875	0.817007
4	MEAND4	4.5	6.55	5.0625	0.993626
4	MEAND5	5.8	8.2	6.4625	1.160011
4	MEAND6	6.7	10	7.7125	1.535347
4	MEAND7	8.2	11.6	9.1125	1.659505
4	MEAND8	9.3	13.25	10.3875	1.912405
4	MEAND9	10.65	14.7	11.7125	1.992643
4	MEAND10	11.65	16.55	13.0875	2.309176
Worker=18					
N Obs	Variable	Minimum	Maximum	Mean	Std Dev
2	MEAND1	1.3	1.35	1.325	0.035355
2	MEAND2	2.65	3.1	2.875	0.318198
2	MEAND3	3.8	4.9	4.35	0.777818
2	MEAND4	5	6.55	5.775	1.096016
2	MEAND5	6	8.8	7.4	1.979899
2	MEAND6	7.7	11.2	9.45	2.474874
2	MEAND7	8.9	12.45	10.675	2.510229
2	MEAND8	10.05	13.7	11.875	2.58094
2	MEAND9	11.15	16.35	13.75	3.676955
2	MEAND10	12.25	17.7	14.975	3.853732
Worker=19					
N Obs	Variable	Minimum	Maximum	Mean	Std Dev
2	MEAND1	1	1.35	1.175	0.247487
2	MEAND2	2.25	2.4	2.325	0.106066
2	MEAND3	3.5	3.8	3.65	0.212132
2	MEAND4	4.7	4.8	4.75	0.070711
2	MEAND5	5.7	6.5	6.1	0.565685
2	MEAND6	7.1	8	7.55	0.636396
2	MEAND7	7.9	9.55	8.725	1.166726
2	MEAND8	9.25	10.75	10	1.06066
2	MEAND9	10.4	12.3	11.35	1.343503
2	MEAND10	11.6	13.7	12.65	1.484924

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Worker=20						
N Obs	Variable	Minimum	Maximum	Mean	Std Dev	
1	MEAND1	1.35	1.35	1.35	.	
1	MEAND2	2.7	2.7	2.7	.	
1	MEAND3	4.15	4.15	4.15	.	
1	MEAND4	5.8	5.8	5.8	.	
1	MEAND5	6.8	6.8	6.8	.	
1	MEAND6	8.65	8.65	8.65	.	
1	MEAND7	10	10	10	.	
1	MEAND8	11.35	11.35	11.35	.	
1	MEAND9	12.75	12.75	12.75	.	
1	MEAND10	14.3	14.3	14.3	.	
Worker=21						
N Obs	Variable	Minimum	Maximum	Mean	Std Dev	
4	MEAND1	1	1.9	1.2875	0.425	
4	MEAND2	1.9	3.2	2.4	0.594419	
4	MEAND3	2.95	5.25	3.7125	1.073449	
4	MEAND4	3.9	6.25	4.8	1.097725	
4	MEAND5	4.8	8.55	6.1625	1.725	
4	MEAND6	5.8	9.8	7.2125	1.84046	
4	MEAND7	6.85	11.5	8.475	2.158124	
4	MEAND8	7.8	13.15	9.65	2.47622	
4	MEAND9	8.95	15.4	11.1125	3.028854	
4	MEAND10	9.95	16.9	12.2625	3.264806	
Worker=22						
N Obs	Variable	Minimum	Maximum	Mean	Std Dev	
2	MEAND1	1.65	1.75	1.7	0.070711	
2	MEAND2	3.3	3.4	3.35	0.070711	
2	MEAND3	4.9	5	4.95	0.070711	
2	MEAND4	6.05	6.55	6.3	0.353553	
2	MEAND5	7.3	8.6	7.95	0.919239	
2	MEAND6	8.35	10.8	9.575	1.732412	
2	MEAND7	10.45	13.1	11.775	1.873833	
2	MEAND8	11.8	14.8	13.3	2.12132	
2	MEAND9	13	16.6	14.8	2.545584	
2	MEAND10	14.5	18.4	16.45	2.757716	

Worker=23					
N Obs	Variable	Minimum	Maximum	Mean	Std Dev
5	MEAND1	1.25	1.65	1.45	0.145774
5	MEAND2	2.55	3.45	2.92	0.420714
5	MEAND3	3.7	5.4	4.45	0.649038
5	MEAND4	5.2	7.35	5.98	0.906642
5	MEAND5	6.3	9	7.23	1.101476
5	MEAND6	7.1	10.55	8.72	1.28676
5	MEAND7	8.55	12.3	10.18	1.473347
5	MEAND8	9.75	13.45	11.36	1.425833
5	MEAND9	10.95	15.5	12.94	1.878963
5	MEAND10	12.25	17.15	14.42	2.048658
Worker=24					
N Obs	Variable	Minimum	Maximum	Mean	Std Dev
6	MEAND1	1.15	2.35	1.683333	0.467618
6	MEAND2	2.45	4.4	3.258333	0.733087
6	MEAND3	4.1	5.9	4.7	0.694982
6	MEAND4	4.85	8.45	6.358333	1.598254
6	MEAND5	6.55	9.95	8.083333	1.66002
6	MEAND6	7.7	11.8	9.525	1.831325
6	MEAND7	8.95	14.15	11.225	2.273049
6	MEAND8	10	16.35	12.85	2.686634
6	MEAND9	11.3	18.45	14.44167	3.13519
6	MEAND10	12.45	21.1	16.16667	3.610217
Worker=25					
N Obs	Variable	Minimum	Maximum	Mean	Std Dev
2	MEAND1	1.4	1.5	1.45	0.070711
2	MEAND2	2.55	2.9	2.725	0.247487
2	MEAND3	3.95	4.15	4.05	0.141421
2	MEAND4	4.9	5.45	5.175	0.388909
2	MEAND5	6.35	7	6.675	0.459619
2	MEAND6	7.5	8.3	7.9	0.565685
2	MEAND7	8.45	9.9	9.175	1.025305
2	MEAND8	9.85	11.4	10.625	1.096016
2	MEAND9	10.85	12.65	11.75	1.272792
2	MEAND10	12	14.1	13.05	1.484924

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Worker=26						
N Obs	Variable	Minimum	Maximum	Mean	Std Dev	
6	MEAND1	1.2	1.9	1.55	0.275681	
6	MEAND2	2.55	3.3	2.9	0.304959	
6	MEAND3	3.6	5.55	4.433333	0.785918	
6	MEAND4	5.15	6.9	5.916667	0.742069	
6	MEAND5	6.2	8.75	7.483333	0.970395	
6	MEAND6	7.35	10.65	8.95	1.233288	
6	MEAND7	8.7	12.05	10.35833	1.333198	
6	MEAND8	10.2	13.9	11.95	1.458767	
6	MEAND9	11.5	15.6	13.39167	1.630772	
6	MEAND10	12.8	17.3	14.925	1.77785	
Worker=27						
N Obs	Variable	Minimum	Maximum	Mean	Std Dev	
5	MEAND1	1.15	1.65	1.41	0.221923	
5	MEAND2	2.15	2.95	2.7	0.337268	
5	MEAND3	3.15	5.35	4.12	0.807465	
5	MEAND4	4	6.85	5.43	1.033562	
5	MEAND5	5.15	9	6.91	1.391223	
5	MEAND6	6.3	10.75	8.24	1.616864	
5	MEAND7	7.3	12.25	9.69	1.792136	
5	MEAND8	8.3	13.75	11.07	2.013269	
5	MEAND9	9.45	15.7	12.54	2.256214	
5	MEAND10	10.45	17.7	14.02	2.627404	
Worker=28						
N Obs	Variable	Minimum	Maximum	Mean	Std Dev	
4	MEAND1	1.2	1.45	1.3125	0.110868	
4	MEAND2	2.25	2.7	2.5375	0.201556	
4	MEAND3	3.75	4.05	3.825	0.15	
4	MEAND4	5.15	5.35	5.2625	0.085391	
4	MEAND5	6.25	6.85	6.5375	0.246221	
4	MEAND6	7.7	8.1	7.9125	0.193111	
4	MEAND7	8.95	9.5	9.275	0.253311	
4	MEAND8	10.2	10.95	10.625	0.31225	
4	MEAND9	11.55	12.5	11.9375	0.400781	
4	MEAND10	13	13.8	13.2875	0.352077	

Choralkali-Processing Plant						
Worker=1						
N Obs	Variable	Minimum	Maximum	Mean	Std Dev	
1	MEAND1	1.3	1.3	1.3	.	
1	MEAND2	2.5	2.5	2.5	.	
1	MEAND3	4.3	4.3	4.3	.	
1	MEAND4	5.5	5.5	5.5	.	
1	MEAND5	7	7	7	.	
1	MEAND6	8.3	8.3	8.3	.	
1	MEAND7	9.6	9.6	9.6	.	
1	MEAND8	11	11	11	.	
1	MEAND9	12.5	12.5	12.5	.	
1	MEAND10	14	14	14	.	
Worker=2						
N Obs	Variable	Minimum	Maximum	Mean	Std Dev	
1	MEAND1	1.4	1.4	1.4	.	
1	MEAND2	2.6	2.6	2.6	.	
1	MEAND3	4.1	4.1	4.1	.	
1	MEAND4	5.5	5.5	5.5	.	
1	MEAND5	7	7	7	.	
1	MEAND6	8.4	8.4	8.4	.	
1	MEAND7	9.7	9.7	9.7	.	
1	MEAND8	11.1	11.1	11.1	.	
1	MEAND9	12.6	12.6	12.6	.	
1	MEAND10	14	14	14	.	
Worker=3						
N Obs	Variable	Minimum	Maximum	Mean	Std Dev	
1	MEAND1	1.2	1.2	1.2	.	
1	MEAND2	2.5	2.5	2.5	.	
1	MEAND3	4.1	4.1	4.1	.	
1	MEAND4	5.5	5.5	5.5	.	
1	MEAND5	7	7	7	.	
1	MEAND6	8.4	8.4	8.4	.	
1	MEAND7	9.8	9.8	9.8	.	
1	MEAND8	11.1	11.1	11.1	.	
1	MEAND9	12.5	12.5	12.5	.	
1	MEAND10	14	14	14	.	

Worker=4						
N Obs	Variable	Minimum	Maximum	Mean	Std Dev	
1	MEAND1	1.3	1.3	1.3	.	
1	MEAND2	2.7	2.7	2.7	.	
1	MEAND3	4	4	4	.	
1	MEAND4	5.7	5.7	5.7	.	
1	MEAND5	7	7	7	.	
1	MEAND6	8.4	8.4	8.4	.	
1	MEAND7	9.7	9.7	9.7	.	
1	MEAND8	11.1	11.1	11.1	.	
1	MEAND9	12.5	12.5	12.5	.	
1	MEAND10	14	14	14	.	
Worker=5						
N Obs	Variable	Minimum	Maximum	Mean	Std Dev	
1	MEAND1	1.4	1.4	1.4	.	
1	MEAND2	2.6	2.6	2.6	.	
1	MEAND3	4.1	4.1	4.1	.	
1	MEAND4	5.5	5.5	5.5	.	
1	MEAND5	7	7	7	.	
1	MEAND6	8.4	8.4	8.4	.	
1	MEAND7	9.7	9.7	9.7	.	
1	MEAND8	11.1	11.1	11.1	.	
1	MEAND9	12.6	12.6	12.6	.	
1	MEAND10	14	14	14	.	
Worker=6						
N Obs	Variable	Minimum	Maximum	Mean	Std Dev	
1	MEAND1	1.55	1.55	1.55	.	
1	MEAND2	2.95	2.95	2.95	.	
1	MEAND3	4.55	4.55	4.55	.	
1	MEAND4	5.9	5.9	5.9	.	
1	MEAND5	7.45	7.45	7.45	.	
1	MEAND6	8.85	8.85	8.85	.	
1	MEAND7	10.45	10.45	10.45	.	
1	MEAND8	11.9	11.9	11.9	.	
1	MEAND9	13.4	13.4	13.4	.	
1	MEAND10	14.9	14.9	14.9	.	

Worker=7						
N Obs	Variable	Minimum	Maximum	Mean	Std Dev	
1	MEAND1	1.5	1.5	1.5	.	
1	MEAND2	2.6	2.6	2.6	.	
1	MEAND3	4.3	4.3	4.3	.	
1	MEAND4	5.6	5.6	5.6	.	
1	MEAND5	7	7	7	.	
1	MEAND6	8.3	8.3	8.3	.	
1	MEAND7	9.8	9.8	9.8	.	
1	MEAND8	11.3	11.3	11.3	.	
1	MEAND9	12.6	12.6	12.6	.	
1	MEAND10	14	14	14	.	
Worker=8						
N Obs	Variable	Minimum	Maximum	Mean	Std Dev	
1	MEAND1	1.4	1.4	1.4	.	
1	MEAND2	2.8	2.8	2.8	.	
1	MEAND3	4	4	4	.	
1	MEAND4	5.4	5.4	5.4	.	
1	MEAND5	7	7	7	.	
1	MEAND6	8.4	8.4	8.4	.	
1	MEAND7	9.8	9.8	9.8	.	
1	MEAND8	11.1	11.1	11.1	.	
1	MEAND9	12.5	12.5	12.5	.	
1	MEAND10	14	14	14	.	
Worker=9						
N Obs	Variable	Minimum	Maximum	Mean	Std Dev	
1	MEAND1	1.5	1.5	1.5	.	
1	MEAND2	2.8	2.8	2.8	.	
1	MEAND3	4.2	4.2	4.2	.	
1	MEAND4	5.6	5.6	5.6	.	
1	MEAND5	7	7	7	.	
1	MEAND6	8.3	8.3	8.3	.	
1	MEAND7	9.6	9.6	9.6	.	
1	MEAND8	11	11	11	.	
1	MEAND9	12.5	12.5	12.5	.	
1	MEAND10	14	14	14	.	

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Worker=10						
N Obs	Variable	Minimum	Maximum	Mean	Std Dev	
1	MEAND1	1.65	1.65	1.65	.	
1	MEAND2	3.2	3.2	3.2	.	
1	MEAND3	4.45	4.45	4.45	.	
1	MEAND4	5.7	5.7	5.7	.	
1	MEAND5	7.3	7.3	7.3	.	
1	MEAND6	8.8	8.8	8.8	.	
1	MEAND7	10.05	10.05	10.05	.	
1	MEAND8	11.55	11.55	11.55	.	
1	MEAND9	13	13	13	.	
1	MEAND10	14.5	14.5	14.5	.	
Worker=11						
N Obs	Variable	Minimum	Maximum	Mean	Std Dev	
1	MEAND1	1.3	1.3	1.3	.	
1	MEAND2	2.7	2.7	2.7	.	
1	MEAND3	4.3	4.3	4.3	.	
1	MEAND4	5.5	5.5	5.5	.	
1	MEAND5	7	7	7	.	
1	MEAND6	8.2	8.2	8.2	.	
1	MEAND7	9.6	9.6	9.6	.	
1	MEAND8	11.1	11.1	11.1	.	
1	MEAND9	12.5	12.5	12.5	.	
1	MEAND10	14	14	14	.	
Worker=12						
N Obs	Variable	Minimum	Maximum	Mean	Std Dev	
1	MEAND1	1.2	1.2	1.2	.	
1	MEAND2	2.9	2.9	2.9	.	
1	MEAND3	4.3	4.3	4.3	.	
1	MEAND4	5.4	5.4	5.4	.	
1	MEAND5	7	7	7	.	
1	MEAND6	8.2	8.2	8.2	.	
1	MEAND7	9.7	9.7	9.7	.	
1	MEAND8	11	11	11	.	
1	MEAND9	12.5	12.5	12.5	.	
1	MEAND10	14	14	14	.	

Worker=13						
N Obs	Variable	Minimum	Maximum	Mean	Std Dev	
1	MEAND1	1.45	1.45	1.45	.	
1	MEAND2	3.45	3.45	3.45	.	
1	MEAND3	5.25	5.25	5.25	.	
1	MEAND4	6.8	6.8	6.8	.	
1	MEAND5	8.55	8.55	8.55	.	
1	MEAND6	10.75	10.75	10.75	.	
1	MEAND7	12.45	12.45	12.45	.	
1	MEAND8	13.7	13.7	13.7	.	
1	MEAND9	15.4	15.4	15.4	.	
1	MEAND10	16.8	16.8	16.8	.	
Worker=14						
N Obs	Variable	Minimum	Maximum	Mean	Std Dev	
1	MEAND1	1.4	1.4	1.4	.	
1	MEAND2	2.7	2.7	2.7	.	
1	MEAND3	4.1	4.1	4.1	.	
1	MEAND4	5.5	5.5	5.5	.	
1	MEAND5	7	7	7	.	
1	MEAND6	8.2	8.2	8.2	.	
1	MEAND7	9.8	9.8	9.8	.	
1	MEAND8	11.1	11.1	11.1	.	
1	MEAND9	12.5	12.5	12.5	.	
1	MEAND10	14	14	14	.	
Worker=15						
N Obs	Variable	Minimum	Maximum	Mean	Std Dev	
1	MEAND1	1.65	1.65	1.65	.	
1	MEAND2	3.05	3.05	3.05	.	
1	MEAND3	4.6	4.6	4.6	.	
1	MEAND4	6.55	6.55	6.55	.	
1	MEAND5	8.05	8.05	8.05	.	
1	MEAND6	10.05	10.05	10.05	.	
1	MEAND7	11.9	11.9	11.9	.	
1	MEAND8	13.55	13.55	13.55	.	
1	MEAND9	14.95	14.95	14.95	.	
1	MEAND10	16.45	16.45	16.45	.	

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Automobile-Manufacturing Plant						
Worker=1						
N Obs	Variable	Minimum	Maximum	Mean	Std Dev	
1	MEAND1	1.55	1.55	1.55	.	
1	MEAND2	3.2	3.2	3.2	.	
1	MEAND3	4.4	4.4	4.4	.	
1	MEAND4	6.2	6.2	6.2	.	
1	MEAND5	8	8	8	.	
1	MEAND6	9.3	9.3	9.3	.	
1	MEAND7	11.25	11.25	11.25	.	
1	MEAND8	12.65	12.65	12.65	.	
1	MEAND9	14.55	14.55	14.55	.	
1	MEAND10	16.1	16.1	16.1	.	
Worker=2						
N Obs	Variable	Minimum	Maximum	Mean	Std Dev	
3	MEAND1	1.35	1.4	1.383333	0.028868	
3	MEAND2	2.85	3.25	3.016667	0.208167	
3	MEAND3	4.2	4.4	4.316667	0.104083	
3	MEAND4	5.65	6.2	5.966667	0.284312	
3	MEAND5	7.35	7.75	7.583333	0.208167	
3	MEAND6	8.85	9.45	9.15	0.3	
3	MEAND7	10.05	11.1	10.58333	0.525198	
3	MEAND8	11.65	13	12.23333	0.693422	
3	MEAND9	13	14.4	13.66667	0.702377	
3	MEAND10	14.45	16.05	15.2	0.804674	
Worker=3						
N Obs	Variable	Minimum	Maximum	Mean	Std Dev	
2	MEAND1	1.45	1.5	1.475	0.035355	
2	MEAND2	2.6	3	2.8	0.282843	
2	MEAND3	4.55	4.8	4.675	0.176777	
2	MEAND4	5.85	6.3	6.075	0.318198	
2	MEAND5	7.25	7.4	7.325	0.106066	
2	MEAND6	8.8	9.3	9.05	0.353553	
2	MEAND7	10.2	10.7	10.45	0.353553	
2	MEAND8	11.55	12.1	11.825	0.388909	
2	MEAND9	13.15	13.8	13.475	0.459619	
2	MEAND10	14.7	15.4	15.05	0.494975	

BREAKDOWN BY TIME SERIES (if more than one time series per worker)						
Pesticide-Production Facility						
Worker=1, Time Series=1						
N Obs	Variable	Minimum	Maximum	Mean	Std Dev	
1	MEAND1	1.1	1.1	1.1	.	
1	MEAND2	2.3	2.3	2.3	.	
1	MEAND3	3.45	3.45	3.45	.	
1	MEAND4	4.35	4.35	4.35	.	
1	MEAND5	5.4	5.4	5.4	.	
1	MEAND6	6.55	6.55	6.55	.	
1	MEAND7	7.75	7.75	7.75	.	
1	MEAND8	8.75	8.75	8.75	.	
1	MEAND9	9.85	9.85	9.85	.	
1	MEAND10	10.9	10.9	10.9	.	
Worker=1, Time Series=2						
N Obs	Variable	Minimum	Maximum	Mean	Std Dev	
1	MEAND1	1.8	1.8	1.8	.	
1	MEAND2	2.95	2.95	2.95	.	
1	MEAND3	4.75	4.75	4.75	.	
1	MEAND4	5.75	5.75	5.75	.	
1	MEAND5	8	8	8	.	
1	MEAND6	8.8	8.8	8.8	.	
1	MEAND7	10.2	10.2	10.2	.	
1	MEAND8	12.05	12.05	12.05	.	
1	MEAND9	13.4	13.4	13.4	.	
1	MEAND10	14.9	14.9	14.9	.	
Worker=1, Time Series=3						
N Obs	Variable	Minimum	Maximum	Mean	Std Dev	
1	MEAND1	1.15	1.15	1.15	.	
1	MEAND2	2.5	2.5	2.5	.	
1	MEAND3	3.55	3.55	3.55	.	
1	MEAND4	4.6	4.6	4.6	.	
1	MEAND5	5.95	5.95	5.95	.	
1	MEAND6	7.1	7.1	7.1	.	
1	MEAND7	8.3	8.3	8.3	.	
1	MEAND8	9.45	9.45	9.45	.	
1	MEAND9	10.6	10.6	10.6	.	

1	MEAND10	11.75	11.75	11.75	.	
Worker=1, Time Series=4						
N Obs	Variable	Minimum	Maximum	Mean	Std Dev	
1	MEAND1	1.25	1.25	1.25	.	
1	MEAND2	2.5	2.5	2.5	.	
1	MEAND3	3.9	3.9	3.9	.	
1	MEAND4	4.8	4.8	4.8	.	
1	MEAND5	6.5	6.5	6.5	.	
1	MEAND6	7.75	7.75	7.75	.	
1	MEAND7	8.7	8.7	8.7	.	
1	MEAND8	9.95	9.95	9.95	.	
1	MEAND9	11.25	11.25	11.25	.	
1	MEAND10	12.35	12.35	12.35	.	
Worker=1, Time Series=5						
N Obs	Variable	Minimum	Maximum	Mean	Std Dev	
1	MEAND1	1.65	1.65	1.65	.	
1	MEAND2	2.7	2.7	2.7	.	
1	MEAND3	4	4	4	.	
1	MEAND4	5.6	5.6	5.6	.	
1	MEAND5	6.8	6.8	6.8	.	
1	MEAND6	8.15	8.15	8.15	.	
1	MEAND7	9.75	9.75	9.75	.	
1	MEAND8	11.1	11.1	11.1	.	
1	MEAND9	12.45	12.45	12.45	.	
1	MEAND10	13.9	13.9	13.9	.	
Worker=1, Time Series=6						
N Obs	Variable	Minimum	Maximum	Mean	Std Dev	
1	MEAND1	1.4	1.4	1.4	.	
1	MEAND2	2.7	2.7	2.7	.	
1	MEAND3	4.45	4.45	4.45	.	
1	MEAND4	6.05	6.05	6.05	.	
1	MEAND5	7.5	7.5	7.5	.	
1	MEAND6	8.9	8.9	8.9	.	
1	MEAND7	10.85	10.85	10.85	.	
1	MEAND8	12.15	12.15	12.15	.	
1	MEAND9	13.7	13.7	13.7	.	
1	MEAND10	15.3	15.3	15.3	.	

Worker=1, Time Series=7						
N Obs	Variable	Minimum	Maximum	Mean	Std Dev	
1	MEAND1	1.7	1.7	1.7	.	
1	MEAND2	3.2	3.2	3.2	.	
1	MEAND3	5.15	5.15	5.15	.	
1	MEAND4	7.3	7.3	7.3	.	
1	MEAND5	8.55	8.55	8.55	.	
1	MEAND6	10.5	10.5	10.5	.	
1	MEAND7	12.2	12.2	12.2	.	
1	MEAND8	13.85	13.85	13.85	.	
1	MEAND9	15.35	15.35	15.35	.	
1	MEAND10	17.05	17.05	17.05	.	
Worker=1, Time Series=8						
N Obs	Variable	Minimum	Maximum	Mean	Std Dev	
1	MEAND1	1.4	1.4	1.4	.	
1	MEAND2	3.35	3.35	3.35	.	
1	MEAND3	4.55	4.55	4.55	.	
1	MEAND4	5.95	5.95	5.95	.	
1	MEAND5	7.5	7.5	7.5	.	
1	MEAND6	9	9	9	.	
1	MEAND7	10.6	10.6	10.6	.	
1	MEAND8	12.1	12.1	12.1	.	
1	MEAND9	13.7	13.7	13.7	.	
1	MEAND10	15.15	15.15	15.15	.	
Worker=6, Time Series=1						
N Obs	Variable	Minimum	Maximum	Mean	Std Dev	
1	MEAND1	1.25	1.25	1.25	.	
1	MEAND2	3.2	3.2	3.2	.	
1	MEAND3	4.65	4.65	4.65	.	
1	MEAND4	6.45	6.45	6.45	.	
1	MEAND5	8.15	8.15	8.15	.	
1	MEAND6	10.25	10.25	10.25	.	
1	MEAND7	11.15	11.15	11.15	.	
1	MEAND8	13.15	13.15	13.15	.	
1	MEAND9	14.65	14.65	14.65	.	
1	MEAND10	16.1	16.1	16.1	.	

Worker=6, Time Series=2						
N Obs	Variable	Minimum	Maximum	Mean	Std Dev	
1	MEAND1	1.25	1.25	1.25	.	
1	MEAND2	2.9	2.9	2.9	.	
1	MEAND3	4.35	4.35	4.35	.	
1	MEAND4	5.4	5.4	5.4	.	
1	MEAND5	6.9	6.9	6.9	.	
1	MEAND6	8.7	8.7	8.7	.	
1	MEAND7	9.8	9.8	9.8	.	
1	MEAND8	11.65	11.65	11.65	.	
1	MEAND9	12.85	12.85	12.85	.	
1	MEAND10	14.45	14.45	14.45	.	
Worker=6, Time Series=3						
N Obs	Variable	Minimum	Maximum	Mean	Std Dev	
1	MEAND1	1.6	1.6	1.6	.	
1	MEAND2	3.05	3.05	3.05	.	
1	MEAND3	4.6	4.6	4.6	.	
1	MEAND4	5.9	5.9	5.9	.	
1	MEAND5	7.75	7.75	7.75	.	
1	MEAND6	9.25	9.25	9.25	.	
1	MEAND7	10.6	10.6	10.6	.	
1	MEAND8	12.45	12.45	12.45	.	
1	MEAND9	13.85	13.85	13.85	.	
1	MEAND10	15.6	15.6	15.6	.	
Worker=6, Time Series=4						
N Obs	Variable	Minimum	Maximum	Mean	Std Dev	
1	MEAND1	1.2	1.2	1.2	.	
1	MEAND2	2.35	2.35	2.35	.	
1	MEAND3	3.7	3.7	3.7	.	
1	MEAND4	4.75	4.75	4.75	.	
1	MEAND5	6.05	6.05	6.05	.	
1	MEAND6	7.15	7.15	7.15	.	
1	MEAND7	8.4	8.4	8.4	.	
1	MEAND8	9.7	9.7	9.7	.	
1	MEAND9	10.95	10.95	10.95	.	
1	MEAND10	12.2	12.2	12.2	.	

Worker=6, Time Series=5						
N Obs	Variable	Minimum	Maximum	Mean	Std Dev	
1	MEAND1	1.05	1.05	1.05	.	
1	MEAND2	2.2	2.2	2.2	.	
1	MEAND3	3.1	3.1	3.1	.	
1	MEAND4	4.45	4.45	4.45	.	
1	MEAND5	5.4	5.4	5.4	.	
1	MEAND6	6.45	6.45	6.45	.	
1	MEAND7	7.6	7.6	7.6	.	
1	MEAND8	8.6	8.6	8.6	.	
1	MEAND9	10	10	10	.	
1	MEAND10	11.05	11.05	11.05	.	
Worker=6, Time Series=6						
N Obs	Variable	Minimum	Maximum	Mean	Std Dev	
1	MEAND1	1.85	1.85	1.85	.	
1	MEAND2	3.25	3.25	3.25	.	
1	MEAND3	4.85	4.85	4.85	.	
1	MEAND4	6.75	6.75	6.75	.	
1	MEAND5	7.8	7.8	7.8	.	
1	MEAND6	9.75	9.75	9.75	.	
1	MEAND7	11.45	11.45	11.45	.	
1	MEAND8	13.15	13.15	13.15	.	
1	MEAND9	14.5	14.5	14.5	.	
1	MEAND10	16.45	16.45	16.45	.	
Worker=6, Time Series=7						
N Obs	Variable	Minimum	Maximum	Mean	Std Dev	
1	MEAND1	1.45	1.45	1.45	.	
1	MEAND2	3.1	3.1	3.1	.	
1	MEAND3	5	5	5	.	
1	MEAND4	6.85	6.85	6.85	.	
1	MEAND5	8.45	8.45	8.45	.	
1	MEAND6	10.3	10.3	10.3	.	
1	MEAND7	11.9	11.9	11.9	.	
1	MEAND8	13.7	13.7	13.7	.	
1	MEAND9	15.6	15.6	15.6	.	
1	MEAND10	17.25	17.25	17.25	.	

Worker=6, Time Series=8						
N Obs	Variable	Minimum	Maximum	Mean	Std Dev	
1	MEAND1	1.4	1.4	1.4	.	
1	MEAND2	2.6	2.6	2.6	.	
1	MEAND3	3.9	3.9	3.9	.	
1	MEAND4	4.9	4.9	4.9	.	
1	MEAND5	6.2	6.2	6.2	.	
1	MEAND6	7.6	7.6	7.6	.	
1	MEAND7	8.9	8.9	8.9	.	
1	MEAND8	10.2	10.2	10.2	.	
1	MEAND9	11.4	11.4	11.4	.	
1	MEAND10	12.6	12.6	12.6	.	
Worker=7, Time Series=1						
N Obs	Variable	Minimum	Maximum	Mean	Std Dev	
1	MEAND1	1	1	1	.	
1	MEAND2	2.4	2.4	2.4	.	
1	MEAND3	3	3	3	.	
1	MEAND4	4.6	4.6	4.6	.	
1	MEAND5	5.8	5.8	5.8	.	
1	MEAND6	7.2	7.2	7.2	.	
1	MEAND7	8	8	8	.	
1	MEAND8	9	9	9	.	
1	MEAND9	10	10	10	.	
1	MEAND10	11.2	11.2	11.2	.	
Worker=7, Time Series=2						
N Obs	Variable	Minimum	Maximum	Mean	Std Dev	
1	MEAND1	1.55	1.55	1.55	.	
1	MEAND2	3.6	3.6	3.6	.	
1	MEAND3	5	5	5	.	
1	MEAND4	6.45	6.45	6.45	.	
1	MEAND5	8.3	8.3	8.3	.	
1	MEAND6	9.8	9.8	9.8	.	
1	MEAND7	11.6	11.6	11.6	.	
1	MEAND8	13.35	13.35	13.35	.	
1	MEAND9	15.45	15.45	15.45	.	
1	MEAND10	17.1	17.1	17.1	.	

Worker=7, Time Series=3						
N Obs	Variable	Minimum	Maximum	Mean	Std Dev	
1	MEAND1	1.35	1.35	1.35	.	
1	MEAND2	3.3	3.3	3.3	.	
1	MEAND3	5.4	5.4	5.4	.	
1	MEAND4	6.65	6.65	6.65	.	
1	MEAND5	8.4	8.4	8.4	.	
1	MEAND6	10	10	10	.	
1	MEAND7	10.9	10.9	10.9	.	
1	MEAND8	12.55	12.55	12.55	.	
1	MEAND9	14.1	14.1	14.1	.	
1	MEAND10	15.75	15.75	15.75	.	
Worker=7, Time Series=4						
N Obs	Variable	Minimum	Maximum	Mean	Std Dev	
1	MEAND1	1.65	1.65	1.65	.	
1	MEAND2	2.7	2.7	2.7	.	
1	MEAND3	5	5	5	.	
1	MEAND4	6	6	6	.	
1	MEAND5	7.95	7.95	7.95	.	
1	MEAND6	9	9	9	.	
1	MEAND7	10.9	10.9	10.9	.	
1	MEAND8	12.95	12.95	12.95	.	
1	MEAND9	14.55	14.55	14.55	.	
1	MEAND10	16.25	16.25	16.25	.	
Worker=7, Time Series=5						
N Obs	Variable	Minimum	Maximum	Mean	Std Dev	
1	MEAND1	1.5	1.5	1.5	.	
1	MEAND2	2.5	2.5	2.5	.	
1	MEAND3	3.9	3.9	3.9	.	
1	MEAND4	5.5	5.5	5.5	.	
1	MEAND5	7.05	7.05	7.05	.	
1	MEAND6	8.9	8.9	8.9	.	
1	MEAND7	10.35	10.35	10.35	.	
1	MEAND8	11.85	11.85	11.85	.	
1	MEAND9	12.85	12.85	12.85	.	
1	MEAND10	14.55	14.55	14.55	.	

Appendix A

Worker=7, Time Series=6						
N Obs	Variable	Minimum	Maximum	Mean	Std Dev	
1	MEAND1	1.05	1.05	1.05	.	
1	MEAND2	2.15	2.15	2.15	.	
1	MEAND3	3	3	3	.	
1	MEAND4	4	4	4	.	
1	MEAND5	5.2	5.2	5.2	.	
1	MEAND6	6.2	6.2	6.2	.	
1	MEAND7	7.3	7.3	7.3	.	
1	MEAND8	8.1	8.1	8.1	.	
1	MEAND9	9.25	9.25	9.25	.	
1	MEAND10	10.15	10.15	10.15	.	
Worker=7, Time Series=7						
N Obs	Variable	Minimum	Maximum	Mean	Std Dev	
1	MEAND1	0.8	0.8	0.8	.	
1	MEAND2	1.8	1.8	1.8	.	
1	MEAND3	2.65	2.65	2.65	.	
1	MEAND4	3.4	3.4	3.4	.	
1	MEAND5	4.2	4.2	4.2	.	
1	MEAND6	5	5	5	.	
1	MEAND7	5.85	5.85	5.85	.	
1	MEAND8	6.65	6.65	6.65	.	
1	MEAND9	7.45	7.45	7.45	.	
1	MEAND10	8.25	8.25	8.25	.	
Worker=7, Time Series=8						
N Obs	Variable	Minimum	Maximum	Mean	Std Dev	
1	MEAND1	1.4	1.4	1.4	.	
1	MEAND2	3.1	3.1	3.1	.	
1	MEAND3	4.6	4.6	4.6	.	
1	MEAND4	5.9	5.9	5.9	.	
1	MEAND5	7.6	7.6	7.6	.	
1	MEAND6	9.2	9.2	9.2	.	
1	MEAND7	10.4	10.4	10.4	.	
1	MEAND8	12	12	12	.	
1	MEAND9	13.7	13.7	13.7	.	
1	MEAND10	15.2	15.2	15.2	.	

Worker=7, Time Series=9						
N Obs	Variable	Minimum	Maximum	Mean	Std Dev	
1	MEAND1	1.35	1.35	1.35	.	
1	MEAND2	3.15	3.15	3.15	.	
1	MEAND3	5.05	5.05	5.05	.	
1	MEAND4	6.35	6.35	6.35	.	
1	MEAND5	8.1	8.1	8.1	.	
1	MEAND6	10.1	10.1	10.1	.	
1	MEAND7	11.5	11.5	11.5	.	
1	MEAND8	12.7	12.7	12.7	.	
1	MEAND9	14.35	14.35	14.35	.	
1	MEAND10	16.2	16.2	16.2	.	
Worker=9, Time Series=1						
N Obs	Variable	Minimum	Maximum	Mean	Std Dev	
1	MEAND1	1.15	1.15	1.15	.	
1	MEAND2	2.95	2.95	2.95	.	
1	MEAND3	4.3	4.3	4.3	.	
1	MEAND4	5.55	5.55	5.55	.	
1	MEAND5	7.15	7.15	7.15	.	
1	MEAND6	8.7	8.7	8.7	.	
1	MEAND7	9.95	9.95	9.95	.	
1	MEAND8	11.45	11.45	11.45	.	
1	MEAND9	13.05	13.05	13.05	.	
1	MEAND10	14.4	14.4	14.4	.	
Worker=9, Time Series=2						
N Obs	Variable	Minimum	Maximum	Mean	Std Dev	
1	MEAND1	1.15	1.15	1.15	.	
1	MEAND2	3	3	3	.	
1	MEAND3	4.15	4.15	4.15	.	
1	MEAND4	5.9	5.9	5.9	.	
1	MEAND5	7.4	7.4	7.4	.	
1	MEAND6	8.7	8.7	8.7	.	
1	MEAND7	10.65	10.65	10.65	.	
1	MEAND8	12.05	12.05	12.05	.	
1	MEAND9	13.5	13.5	13.5	.	
1	MEAND10	14.95	14.95	14.95	.	

Worker=9, Time Series=3						
N Obs	Variable	Minimum	Maximum	Mean	Std Dev	
1	MEAND1	1.35	1.35	1.35	.	
1	MEAND2	2.85	2.85	2.85	.	
1	MEAND3	4.3	4.3	4.3	.	
1	MEAND4	5.9	5.9	5.9	.	
1	MEAND5	7.55	7.55	7.55	.	
1	MEAND6	8.85	8.85	8.85	.	
1	MEAND7	11	11	11	.	
1	MEAND8	11.95	11.95	11.95	.	
1	MEAND9	13.35	13.35	13.35	.	
1	MEAND10	14.9	14.9	14.9	.	
Worker=9, Time Series=4						
N Obs	Variable	Minimum	Maximum	Mean	Std Dev	
1	MEAND1	1.1	1.1	1.1	.	
1	MEAND2	2.25	2.25	2.25	.	
1	MEAND3	3.25	3.25	3.25	.	
1	MEAND4	4.25	4.25	4.25	.	
1	MEAND5	5.75	5.75	5.75	.	
1	MEAND6	6.65	6.65	6.65	.	
1	MEAND7	7.55	7.55	7.55	.	
1	MEAND8	8.65	8.65	8.65	.	
1	MEAND9	9.6	9.6	9.6	.	
1	MEAND10	10.5	10.5	10.5	.	
Worker=9, Time Series=5						
N Obs	Variable	Minimum	Maximum	Mean	Std Dev	
1	MEAND1	1.15	1.15	1.15	.	
1	MEAND2	2.2	2.2	2.2	.	
1	MEAND3	3.25	3.25	3.25	.	
1	MEAND4	4.1	4.1	4.1	.	
1	MEAND5	5.15	5.15	5.15	.	
1	MEAND6	6.2	6.2	6.2	.	
1	MEAND7	6.95	6.95	6.95	.	
1	MEAND8	7.85	7.85	7.85	.	
1	MEAND9	9	9	9	.	
1	MEAND10	9.9	9.9	9.9	.	

Worker=9, Time Series=6						
N Obs	Variable	Minimum	Maximum	Mean	Std Dev	
1	MEAND1	1.35	1.35	1.35	.	
1	MEAND2	2.85	2.85	2.85	.	
1	MEAND3	4.1	4.1	4.1	.	
1	MEAND4	5.5	5.5	5.5	.	
1	MEAND5	6.85	6.85	6.85	.	
1	MEAND6	7.9	7.9	7.9	.	
1	MEAND7	9.35	9.35	9.35	.	
1	MEAND8	10.75	10.75	10.75	.	
1	MEAND9	12.2	12.2	12.2	.	
1	MEAND10	13.5	13.5	13.5	.	
Worker=9, Time Series=7						
N Obs	Variable	Minimum	Maximum	Mean	Std Dev	
1	MEAND1	1.25	1.25	1.25	.	
1	MEAND2	3.4	3.4	3.4	.	
1	MEAND3	4.8	4.8	4.8	.	
1	MEAND4	6.65	6.65	6.65	.	
1	MEAND5	8	8	8	.	
1	MEAND6	9.7	9.7	9.7	.	
1	MEAND7	11.2	11.2	11.2	.	
1	MEAND8	13.05	13.05	13.05	.	
1	MEAND9	14.25	14.25	14.25	.	
1	MEAND10	15.9	15.9	15.9	.	
Worker=9, Time Series=8						
N Obs	Variable	Minimum	Maximum	Mean	Std Dev	
1	MEAND1	1.45	1.45	1.45	.	
1	MEAND2	2.8	2.8	2.8	.	
1	MEAND3	4.55	4.55	4.55	.	
1	MEAND4	6.15	6.15	6.15	.	
1	MEAND5	7.5	7.5	7.5	.	
1	MEAND6	8.95	8.95	8.95	.	
1	MEAND7	10.25	10.25	10.25	.	
1	MEAND8	11.75	11.75	11.75	.	
1	MEAND9	13.1	13.1	13.1	.	
1	MEAND10	14.7	14.7	14.7	.	

Worker=10, Time Series=1					
N Obs	Variable	Minimum	Maximum	Mean	Std Dev
1	MEAND1	1.1	1.1	1.1	.
1	MEAND2	2.05	2.05	2.05	.
1	MEAND3	3.15	3.15	3.15	.
1	MEAND4	4.4	4.4	4.4	.
1	MEAND5	5.35	5.35	5.35	.
1	MEAND6	6.2	6.2	6.2	.
1	MEAND7	7.25	7.25	7.25	.
1	MEAND8	8.25	8.25	8.25	.
1	MEAND9	9.2	9.2	9.2	.
1	MEAND10	10.1	10.1	10.1	.
Worker=10, Time Series=2					
N Obs	Variable	Minimum	Maximum	Mean	Std Dev
1	MEAND1	1.25	1.25	1.25	.
1	MEAND2	2.65	2.65	2.65	.
1	MEAND3	3.9	3.9	3.9	.
1	MEAND4	5.25	5.25	5.25	.
1	MEAND5	6.7	6.7	6.7	.
1	MEAND6	8.25	8.25	8.25	.
1	MEAND7	9.55	9.55	9.55	.
1	MEAND8	11.1	11.1	11.1	.
1	MEAND9	12.6	12.6	12.6	.
1	MEAND10	13.85	13.85	13.85	.
Worker=10, Time Series=3					
N Obs	Variable	Minimum	Maximum	Mean	Std Dev
1	MEAND1	1.4	1.4	1.4	.
1	MEAND2	2.8	2.8	2.8	.
1	MEAND3	4.65	4.65	4.65	.
1	MEAND4	5.6	5.6	5.6	.
1	MEAND5	7.8	7.8	7.8	.
1	MEAND6	8.75	8.75	8.75	.
1	MEAND7	10.25	10.25	10.25	.
1	MEAND8	12.2	12.2	12.2	.
1	MEAND9	13.65	13.65	13.65	.
1	MEAND10	15.65	15.65	15.65	.

Worker=10, Time Series=4						
N Obs	Variable	Minimum	Maximum	Mean	Std Dev	
1	MEAND1	1.4	1.4	1.4	.	
1	MEAND2	3.15	3.15	3.15	.	
1	MEAND3	4.6	4.6	4.6	.	
1	MEAND4	6	6	6	.	
1	MEAND5	7.6	7.6	7.6	.	
1	MEAND6	9.25	9.25	9.25	.	
1	MEAND7	11.25	11.25	11.25	.	
1	MEAND8	12.9	12.9	12.9	.	
1	MEAND9	14.3	14.3	14.3	.	
1	MEAND10	16.05	16.05	16.05	.	
Worker=10, Time Series=5						
N Obs	Variable	Minimum	Maximum	Mean	Std Dev	
1	MEAND1	1.25	1.25	1.25	.	
1	MEAND2	2.4	2.4	2.4	.	
1	MEAND3	3.75	3.75	3.75	.	
1	MEAND4	4.85	4.85	4.85	.	
1	MEAND5	6	6	6	.	
1	MEAND6	7.3	7.3	7.3	.	
1	MEAND7	8.55	8.55	8.55	.	
1	MEAND8	9.95	9.95	9.95	.	
1	MEAND9	11.4	11.4	11.4	.	
1	MEAND10	12.6	12.6	12.6	.	
Worker=10, Time Series=6						
N Obs	Variable	Minimum	Maximum	Mean	Std Dev	
1	MEAND1	1.2	1.2	1.2	.	
1	MEAND2	2.85	2.85	2.85	.	
1	MEAND3	4.8	4.8	4.8	.	
1	MEAND4	5.7	5.7	5.7	.	
1	MEAND5	7.25	7.25	7.25	.	
1	MEAND6	8.8	8.8	8.8	.	
1	MEAND7	10.35	10.35	10.35	.	
1	MEAND8	12	12	12	.	
1	MEAND9	13.55	13.55	13.55	.	
1	MEAND10	14.95	14.95	14.95	.	

Worker=10, Time Series=7						
N Obs	Variable	Minimum	Maximum	Mean	Std Dev	
1	MEAND1	1	1	1	.	
1	MEAND2	1.95	1.95	1.95	.	
1	MEAND3	3	3	3	.	
1	MEAND4	3.95	3.95	3.95	.	
1	MEAND5	5.05	5.05	5.05	.	
1	MEAND6	5.85	5.85	5.85	.	
1	MEAND7	6.9	6.9	6.9	.	
1	MEAND8	7.8	7.8	7.8	.	
1	MEAND9	8.65	8.65	8.65	.	
1	MEAND10	9.65	9.65	9.65	.	
Worker=10, Time Series=8						
N Obs	Variable	Minimum	Maximum	Mean	Std Dev	
1	MEAND1	1.3	1.3	1.3	.	
1	MEAND2	2.75	2.75	2.75	.	
1	MEAND3	4.1	4.1	4.1	.	
1	MEAND4	5.55	5.55	5.55	.	
1	MEAND5	6.95	6.95	6.95	.	
1	MEAND6	8.2	8.2	8.2	.	
1	MEAND7	9.35	9.35	9.35	.	
1	MEAND8	10.85	10.85	10.85	.	
1	MEAND9	12.1	12.1	12.1	.	
1	MEAND10	13.4	13.4	13.4	.	
Worker=10, Time Series=9						
N Obs	Variable	Minimum	Maximum	Mean	Std Dev	
1	MEAND1	1.9	1.9	1.9	.	
1	MEAND2	3.3	3.3	3.3	.	
1	MEAND3	4.85	4.85	4.85	.	
1	MEAND4	7.45	7.45	7.45	.	
1	MEAND5	8.3	8.3	8.3	.	
1	MEAND6	10.35	10.35	10.35	.	
1	MEAND7	12.05	12.05	12.05	.	
1	MEAND8	13.3	13.3	13.3	.	
1	MEAND9	15.4	15.4	15.4	.	
1	MEAND10	17.05	17.05	17.05	.	

Worker=10, Time Series=10						
N Obs	Variable	Minimum	Maximum	Mean	Std Dev	
1	MEAND1	1.8	1.8	1.8	.	
1	MEAND2	3.3	3.3	3.3	.	
1	MEAND3	4.9	4.9	4.9	.	
1	MEAND4	5.6	5.6	5.6	.	
1	MEAND5	7.5	7.5	7.5	.	
1	MEAND6	8.9	8.9	8.9	.	
1	MEAND7	10.6	10.6	10.6	.	
1	MEAND8	12.15	12.15	12.15	.	
1	MEAND9	13.9	13.9	13.9	.	
1	MEAND10	15.55	15.55	15.55	.	
Worker=11, Time Series=1						
N Obs	Variable	Minimum	Maximum	Mean	Std Dev	
1	MEAND1	1.45	1.45	1.45	.	
1	MEAND2	2.9	2.9	2.9	.	
1	MEAND3	4.15	4.15	4.15	.	
1	MEAND4	5.55	5.55	5.55	.	
1	MEAND5	7.15	7.15	7.15	.	
1	MEAND6	8.6	8.6	8.6	.	
1	MEAND7	9.75	9.75	9.75	.	
1	MEAND8	11.4	11.4	11.4	.	
1	MEAND9	12.8	12.8	12.8	.	
1	MEAND10	14.15	14.15	14.15	.	
Worker=11, Time Series=2						
N Obs	Variable	Minimum	Maximum	Mean	Std Dev	
1	MEAND1	1.3	1.3	1.3	.	
1	MEAND2	2.9	2.9	2.9	.	
1	MEAND3	3.8	3.8	3.8	.	
1	MEAND4	5.7	5.7	5.7	.	
1	MEAND5	6.95	6.95	6.95	.	
1	MEAND6	8.55	8.55	8.55	.	
1	MEAND7	9.85	9.85	9.85	.	
1	MEAND8	11.35	11.35	11.35	.	
1	MEAND9	12.5	12.5	12.5	.	
1	MEAND10	13.85	13.85	13.85	.	

Appendix A

Worker=11, Time Series=3						
N Obs	Variable	Minimum	Maximum	Mean	Std Dev	
1	MEAND1	1.1	1.1	1.1	.	
1	MEAND2	3	3	3	.	
1	MEAND3	4.55	4.55	4.55	.	
1	MEAND4	5.6	5.6	5.6	.	
1	MEAND5	6.55	6.55	6.55	.	
1	MEAND6	8.65	8.65	8.65	.	
1	MEAND7	10.6	10.6	10.6	.	
1	MEAND8	11.6	11.6	11.6	.	
1	MEAND9	12.65	12.65	12.65	.	
1	MEAND10	14	14	14	.	
Worker=11, Time Series=4						
N Obs	Variable	Minimum	Maximum	Mean	Std Dev	
1	MEAND1	1.2	1.2	1.2	.	
1	MEAND2	2.7	2.7	2.7	.	
1	MEAND3	3.7	3.7	3.7	.	
1	MEAND4	5.15	5.15	5.15	.	
1	MEAND5	6.6	6.6	6.6	.	
1	MEAND6	7.75	7.75	7.75	.	
1	MEAND7	8.95	8.95	8.95	.	
1	MEAND8	10.1	10.1	10.1	.	
1	MEAND9	11.5	11.5	11.5	.	
1	MEAND10	13	13	13	.	
Worker=11, Time Series=5						
N Obs	Variable	Minimum	Maximum	Mean	Std Dev	
1	MEAND1	2	2	2	.	
1	MEAND2	3.1	3.1	3.1	.	
1	MEAND3	5.55	5.55	5.55	.	
1	MEAND4	7.85	7.85	7.85	.	
1	MEAND5	8.75	8.75	8.75	.	
1	MEAND6	11.2	11.2	11.2	.	
1	MEAND7	12.85	12.85	12.85	.	
1	MEAND8	14.75	14.75	14.75	.	
1	MEAND9	16.75	16.75	16.75	.	
1	MEAND10	18.25	18.25	18.25	.	

Worker=11, Time Series=6						
N Obs	Variable	Minimum	Maximum	Mean	Std Dev	
1	MEAND1	1.1	1.1	1.1	.	
1	MEAND2	2.1	2.1	2.1	.	
1	MEAND3	3.2	3.2	3.2	.	
1	MEAND4	4.3	4.3	4.3	.	
1	MEAND5	5.4	5.4	5.4	.	
1	MEAND6	6.3	6.3	6.3	.	
1	MEAND7	7.7	7.7	7.7	.	
1	MEAND8	8.6	8.6	8.6	.	
1	MEAND9	9.7	9.7	9.7	.	
1	MEAND10	10.7	10.7	10.7	.	
Worker=12, Time Series=1						
N Obs	Variable	Minimum	Maximum	Mean	Std Dev	
1	MEAND1	1.6	1.6	1.6	.	
1	MEAND2	2.75	2.75	2.75	.	
1	MEAND3	4.9	4.9	4.9	.	
1	MEAND4	6.35	6.35	6.35	.	
1	MEAND5	7.7	7.7	7.7	.	
1	MEAND6	8.75	8.75	8.75	.	
1	MEAND7	10.4	10.4	10.4	.	
1	MEAND8	11.75	11.75	11.75	.	
1	MEAND9	13.35	13.35	13.35	.	
1	MEAND10	14.85	14.85	14.85	.	
Worker=12, Time Series=2						
N Obs	Variable	Minimum	Maximum	Mean	Std Dev	
1	MEAND1	1.55	1.55	1.55	.	
1	MEAND2	3.1	3.1	3.1	.	
1	MEAND3	4.95	4.95	4.95	.	
1	MEAND4	6.8	6.8	6.8	.	
1	MEAND5	7.5	7.5	7.5	.	
1	MEAND6	9.25	9.25	9.25	.	
1	MEAND7	10.75	10.75	10.75	.	
1	MEAND8	12.55	12.55	12.55	.	
1	MEAND9	13.8	13.8	13.8	.	
1	MEAND10	15.4	15.4	15.4	.	

Worker=13, Time Series=1						
N Obs	Variable	Minimum	Maximum	Mean	Std Dev	
1	MEAND1	1.5	1.5	1.5	.	
1	MEAND2	3.3	3.3	3.3	.	
1	MEAND3	4.65	4.65	4.65	.	
1	MEAND4	6.45	6.45	6.45	.	
1	MEAND5	7.35	7.35	7.35	.	
1	MEAND6	9.35	9.35	9.35	.	
1	MEAND7	11.4	11.4	11.4	.	
1	MEAND8	13.05	13.05	13.05	.	
1	MEAND9	14.6	14.6	14.6	.	
1	MEAND10	16.15	16.15	16.15	.	
Worker=13, Time Series=2						
N Obs	Variable	Minimum	Maximum	Mean	Std Dev	
1	MEAND1	1.3	1.3	1.3	.	
1	MEAND2	3.15	3.15	3.15	.	
1	MEAND3	4.45	4.45	4.45	.	
1	MEAND4	6.35	6.35	6.35	.	
1	MEAND5	7.55	7.55	7.55	.	
1	MEAND6	9.2	9.2	9.2	.	
1	MEAND7	10.8	10.8	10.8	.	
1	MEAND8	12.4	12.4	12.4	.	
1	MEAND9	14.1	14.1	14.1	.	
1	MEAND10	16	16	16	.	
Worker=13, Time Series=3						
N Obs	Variable	Minimum	Maximum	Mean	Std Dev	
1	MEAND1	1.25	1.25	1.25	.	
1	MEAND2	2.65	2.65	2.65	.	
1	MEAND3	3.7	3.7	3.7	.	
1	MEAND4	4.9	4.9	4.9	.	
1	MEAND5	6.35	6.35	6.35	.	
1	MEAND6	7.75	7.75	7.75	.	
1	MEAND7	8.85	8.85	8.85	.	
1	MEAND8	10.25	10.25	10.25	.	
1	MEAND9	12	12	12	.	
1	MEAND10	13.25	13.25	13.25	.	

Worker=13, Time Series=4						
N Obs	Variable	Minimum	Maximum	Mean	Std Dev	
1	MEAND1	1.45	1.45	1.45	.	
1	MEAND2	3.3	3.3	3.3	.	
1	MEAND3	5.1	5.1	5.1	.	
1	MEAND4	7.6	7.6	7.6	.	
1	MEAND5	9.35	9.35	9.35	.	
1	MEAND6	11.4	11.4	11.4	.	
1	MEAND7	12.95	12.95	12.95	.	
1	MEAND8	15.45	15.45	15.45	.	
1	MEAND9	16.95	16.95	16.95	.	
1	MEAND10	19.15	19.15	19.15	.	
Worker=13, Time Series=5						
N Obs	Variable	Minimum	Maximum	Mean	Std Dev	
1	MEAND1	1.4	1.4	1.4	.	
1	MEAND2	3.35	3.35	3.35	.	
1	MEAND3	4.15	4.15	4.15	.	
1	MEAND4	6.05	6.05	6.05	.	
1	MEAND5	7.15	7.15	7.15	.	
1	MEAND6	8.9	8.9	8.9	.	
1	MEAND7	10.9	10.9	10.9	.	
1	MEAND8	12.5	12.5	12.5	.	
1	MEAND9	13.55	13.55	13.55	.	
1	MEAND10	15.35	15.35	15.35	.	
Worker=15, Time Series=1						
N Obs	Variable	Minimum	Maximum	Mean	Std Dev	
1	MEAND1	0.95	0.95	0.95	.	
1	MEAND2	1.9	1.9	1.9	.	
1	MEAND3	2.85	2.85	2.85	.	
1	MEAND4	3.85	3.85	3.85	.	
1	MEAND5	4.75	4.75	4.75	.	
1	MEAND6	5.75	5.75	5.75	.	
1	MEAND7	6.65	6.65	6.65	.	
1	MEAND8	7.6	7.6	7.6	.	
1	MEAND9	8.55	8.55	8.55	.	
1	MEAND10	9.5	9.5	9.5	.	

Worker=15, Time Series=2					
N Obs	Variable	Minimum	Maximum	Mean	Std Dev
1	MEAND1	1.4	1.4	1.4	.
1	MEAND2	2.7	2.7	2.7	.
1	MEAND3	4.05	4.05	4.05	.
1	MEAND4	5.55	5.55	5.55	.
1	MEAND5	6.85	6.85	6.85	.
1	MEAND6	8.1	8.1	8.1	.
1	MEAND7	9.2	9.2	9.2	.
1	MEAND8	10.45	10.45	10.45	.
1	MEAND9	11.8	11.8	11.8	.
1	MEAND10	13.1	13.1	13.1	.
Worker=15, Time Series=3					
N Obs	Variable	Minimum	Maximum	Mean	Std Dev
1	MEAND1	1.3	1.3	1.3	.
1	MEAND2	2.85	2.85	2.85	.
1	MEAND3	4.3	4.3	4.3	.
1	MEAND4	6.2	6.2	6.2	.
1	MEAND5	7.7	7.7	7.7	.
1	MEAND6	9.1	9.1	9.1	.
1	MEAND7	10.15	10.15	10.15	.
1	MEAND8	11.55	11.55	11.55	.
1	MEAND9	13.2	13.2	13.2	.
1	MEAND10	14.55	14.55	14.55	.
Worker=15, Time Series=4					
N Obs	Variable	Minimum	Maximum	Mean	Std Dev
1	MEAND1	1.35	1.35	1.35	.
1	MEAND2	2.9	2.9	2.9	.
1	MEAND3	4	4	4	.
1	MEAND4	5.75	5.75	5.75	.
1	MEAND5	7.15	7.15	7.15	.
1	MEAND6	9	9	9	.
1	MEAND7	10	10	10	.
1	MEAND8	12	12	12	.
1	MEAND9	13.5	13.5	13.5	.
	MEAND10	14.9	14.9	14.9	.

Worker=15, Time Series=5						
N Obs	Variable	Minimum	Maximum	Mean	Std Dev	
1	MEAND1	1.2	1.2	1.2	.	
1	MEAND2	2.75	2.75	2.75	.	
1	MEAND3	4.05	4.05	4.05	.	
1	MEAND4	5.05	5.05	5.05	.	
1	MEAND5	6.95	6.95	6.95	.	
1	MEAND6	8.4	8.4	8.4	.	
1	MEAND7	9.7	9.7	9.7	.	
1	MEAND8	11.15	11.15	11.15	.	
1	MEAND9	12.65	12.65	12.65	.	
1	MEAND10	13.85	13.85	13.85	.	
Worker=15, Time Series=6						
N Obs	Variable	Minimum	Maximum	Mean	Std Dev	
1	MEAND1	1.05	1.05	1.05	.	
1	MEAND2	2.15	2.15	2.15	.	
1	MEAND3	3.05	3.05	3.05	.	
1	MEAND4	4.1	4.1	4.1	.	
1	MEAND5	5.1	5.1	5.1	.	
1	MEAND6	6.25	6.25	6.25	.	
1	MEAND7	7.15	7.15	7.15	.	
1	MEAND8	8.25	8.25	8.25	.	
1	MEAND9	9.2	9.2	9.2	.	
1	MEAND10	10.1	10.1	10.1	.	
Worker=15, Time Series=7						
N Obs	Variable	Minimum	Maximum	Mean	Std Dev	
1	MEAND1	1.65	1.65	1.65	.	
1	MEAND2	2.35	2.35	2.35	.	
1	MEAND3	5.25	5.25	5.25	.	
1	MEAND4	7.15	7.15	7.15	.	
1	MEAND5	7.4	7.4	7.4	.	
1	MEAND6	9.8	9.8	9.8	.	
1	MEAND7	10.45	10.45	10.45	.	
1	MEAND8	13.15	13.15	13.15	.	
1	MEAND9	15	15	15	.	
1	MEAND10	17.5	17.5	17.5	.	

Worker=15, Time Series=8						
N Obs	Variable	Minimum	Maximum	Mean	Std Dev	
1	MEAND1	0.95	0.95	0.95	.	
1	MEAND2	1.85	1.85	1.85	.	
1	MEAND3	2.5	2.5	2.5	.	
1	MEAND4	3.3	3.3	3.3	.	
1	MEAND5	4.25	4.25	4.25	.	
1	MEAND6	4.85	4.85	4.85	.	
1	MEAND7	5.75	5.75	5.75	.	
1	MEAND8	6.55	6.55	6.55	.	
1	MEAND9	7.35	7.35	7.35	.	
1	MEAND10	8.15	8.15	8.15	.	
Worker=15, Time Series=9						
N Obs	Variable	Minimum	Maximum	Mean	Std Dev	
1	MEAND1	1.6	1.6	1.6	.	
1	MEAND2	3.4	3.4	3.4	.	
1	MEAND3	5.35	5.35	5.35	.	
1	MEAND4	7	7	7	.	
1	MEAND5	8.85	8.85	8.85	.	
1	MEAND6	10.25	10.25	10.25	.	
1	MEAND7	12.7	12.7	12.7	.	
1	MEAND8	14.2	14.2	14.2	.	
1	MEAND9	16.25	16.25	16.25	.	
1	MEAND10	18.2	18.2	18.2	.	
Worker=15, Time Series=10						
N Obs	Variable	Minimum	Maximum	Mean	Std Dev	
1	MEAND1	1.15	1.15	1.15	.	
1	MEAND2	2.15	2.15	2.15	.	
1	MEAND3	3.5	3.5	3.5	.	
1	MEAND4	4.5	4.5	4.5	.	
1	MEAND5	5.4	5.4	5.4	.	
1	MEAND6	6.6	6.6	6.6	.	
1	MEAND7	8	8	8	.	
1	MEAND8	9.1	9.1	9.1	.	
1	MEAND9	10.25	10.25	10.25	.	
1	MEAND10	11.35	11.35	11.35	.	

Worker=15, Time Series=11						
N Obs	Variable	Minimum	Maximum	Mean	Std Dev	
1	MEAND1	1.3	1.3	1.3	.	
1	MEAND2	2.8	2.8	2.8	.	
1	MEAND3	4.4	4.4	4.4	.	
1	MEAND4	5.35	5.35	5.35	.	
1	MEAND5	7.15	7.15	7.15	.	
1	MEAND6	8.5	8.5	8.5	.	
1	MEAND7	10.1	10.1	10.1	.	
1	MEAND8	11.65	11.65	11.65	.	
1	MEAND9	13	13	13	.	
1	MEAND10	14.2	14.2	14.2	.	
Worker=15, Time Series=12						
N Obs	Variable	Minimum	Maximum	Mean	Std Dev	
1	MEAND1	1.65	1.65	1.65	.	
1	MEAND2	2.65	2.65	2.65	.	
1	MEAND3	4.25	4.25	4.25	.	
1	MEAND4	6.1	6.1	6.1	.	
1	MEAND5	7.35	7.35	7.35	.	
1	MEAND6	9.05	9.05	9.05	.	
1	MEAND7	10.3	10.3	10.3	.	
1	MEAND8	11.95	11.95	11.95	.	
1	MEAND9	13.55	13.55	13.55	.	
1	MEAND10	15.15	15.15	15.15	.	
Worker=15, Time Series=13						
N Obs	Variable	Minimum	Maximum	Mean	Std Dev	
1	MEAND1	1	1	1	.	
1	MEAND2	2.25	2.25	2.25	.	
1	MEAND3	3.65	3.65	3.65	.	
1	MEAND4	4.75	4.75	4.75	.	
1	MEAND5	6	6	6	.	
1	MEAND6	7.2	7.2	7.2	.	
1	MEAND7	8.35	8.35	8.35	.	
1	MEAND8	9.65	9.65	9.65	.	
1	MEAND9	11.05	11.05	11.05	.	
1	MEAND10	12.2	12.2	12.2	.	

Worker=15, Time Series=14						
N Obs	Variable	Minimum	Maximum	Mean	Std Dev	
1	MEAND1	0.95	0.95	0.95	.	
1	MEAND2	2.1	2.1	2.1	.	
1	MEAND3	3.15	3.15	3.15	.	
1	MEAND4	4.15	4.15	4.15	.	
1	MEAND5	5.3	5.3	5.3	.	
1	MEAND6	6.15	6.15	6.15	.	
1	MEAND7	7.25	7.25	7.25	.	
1	MEAND8	8.3	8.3	8.3	.	
1	MEAND9	9.35	9.35	9.35	.	
1	MEAND10	10.35	10.35	10.35	.	
Worker=17, Time Series=1						
N Obs	Variable	Minimum	Maximum	Mean	Std Dev	
1	MEAND1	1.15	1.15	1.15	.	
1	MEAND2	2.3	2.3	2.3	.	
1	MEAND3	3.45	3.45	3.45	.	
1	MEAND4	4.5	4.5	4.5	.	
1	MEAND5	5.8	5.8	5.8	.	
1	MEAND6	7.1	7.1	7.1	.	
1	MEAND7	8.2	8.2	8.2	.	
1	MEAND8	9.4	9.4	9.4	.	
1	MEAND9	10.65	10.65	10.65	.	
1	MEAND10	11.95	11.95	11.95	.	
Worker=17, Time Series=2						
N Obs	Variable	Minimum	Maximum	Mean	Std Dev	
1	MEAND1	1.1	1.1	1.1	.	
1	MEAND2	2.3	2.3	2.3	.	
1	MEAND3	3.45	3.45	3.45	.	
1	MEAND4	4.65	4.65	4.65	.	
1	MEAND5	5.9	5.9	5.9	.	
1	MEAND6	7.05	7.05	7.05	.	
1	MEAND7	8.35	8.35	8.35	.	
1	MEAND8	9.6	9.6	9.6	.	
1	MEAND9	10.8	10.8	10.8	.	
1	MEAND10	12	12	12	.	

Worker=17, Time Series=3						
N Obs	Variable	Minimum	Maximum	Mean	Std Dev	
1	MEAND1	1.1	1.1	1.1	.	
1	MEAND2	2.3	2.3	2.3	.	
1	MEAND3	3.5	3.5	3.5	.	
1	MEAND4	4.55	4.55	4.55	.	
1	MEAND5	5.95	5.95	5.95	.	
1	MEAND6	6.7	6.7	6.7	.	
1	MEAND7	8.3	8.3	8.3	.	
1	MEAND8	9.3	9.3	9.3	.	
1	MEAND9	10.7	10.7	10.7	.	
1	MEAND10	11.85	11.85	11.85	.	
Worker=17, Time Series=4						
N Obs	Variable	Minimum	Maximum	Mean	Std Dev	
1	MEAND1	1.7	1.7	1.7	.	
1	MEAND2	2.9	2.9	2.9	.	
1	MEAND3	5.1	5.1	5.1	.	
1	MEAND4	6.55	6.55	6.55	.	
1	MEAND5	8.2	8.2	8.2	.	
1	MEAND6	10	10	10	.	
1	MEAND7	11.6	11.6	11.6	.	
1	MEAND8	13.25	13.25	13.25	.	
1	MEAND9	14.7	14.7	14.7	.	
1	MEAND10	16.55	16.55	16.55	.	
Worker=18, Time Series=1						
N Obs	Variable	Minimum	Maximum	Mean	Std Dev	
1	MEAND1	1.3	1.3	1.3	.	
1	MEAND2	3.1	3.1	3.1	.	
1	MEAND3	4.9	4.9	4.9	.	
1	MEAND4	6.55	6.55	6.55	.	
1	MEAND5	8.8	8.8	8.8	.	
1	MEAND6	11.2	11.2	11.2	.	
1	MEAND7	12.45	12.45	12.45	.	
1	MEAND8	13.7	13.7	13.7	.	
1	MEAND9	16.35	16.35	16.35	.	
1	MEAND10	17.7	17.7	17.7	.	

Worker=18, Time Series=2						
N Obs	Variable	Minimum	Maximum	Mean	Std Dev	
1	MEAND1	1.35	1.35	1.35	.	
1	MEAND2	2.65	2.65	2.65	.	
1	MEAND3	3.8	3.8	3.8	.	
1	MEAND4	5	5	5	.	
1	MEAND5	6	6	6	.	
1	MEAND6	7.7	7.7	7.7	.	
1	MEAND7	8.9	8.9	8.9	.	
1	MEAND8	10.05	10.05	10.05	.	
1	MEAND9	11.15	11.15	11.15	.	
1	MEAND10	12.25	12.25	12.25	.	
Worker=19, Time Series=1						
N Obs	Variable	Minimum	Maximum	Mean	Std Dev	
1	MEAND1	1	1	1	.	
1	MEAND2	2.25	2.25	2.25	.	
1	MEAND3	3.5	3.5	3.5	.	
1	MEAND4	4.7	4.7	4.7	.	
1	MEAND5	5.7	5.7	5.7	.	
1	MEAND6	7.1	7.1	7.1	.	
1	MEAND7	7.9	7.9	7.9	.	
1	MEAND8	9.25	9.25	9.25	.	
1	MEAND9	10.4	10.4	10.4	.	
1	MEAND10	11.6	11.6	11.6	.	
Worker=19, Time Series=2						
N Obs	Variable	Minimum	Maximum	Mean	Std Dev	
1	MEAND1	1.35	1.35	1.35	.	
1	MEAND2	2.4	2.4	2.4	.	
1	MEAND3	3.8	3.8	3.8	.	
1	MEAND4	4.8	4.8	4.8	.	
1	MEAND5	6.5	6.5	6.5	.	
1	MEAND6	8	8	8	.	
1	MEAND7	9.55	9.55	9.55	.	
1	MEAND8	10.75	10.75	10.75	.	
1	MEAND9	12.3	12.3	12.3	.	
1	MEAND10	13.7	13.7	13.7	.	

Worker=21, Time Series=1						
N Obs	Variable	Minimum	Maximum	Mean	Std Dev	
1	MEAND1	1	1	1	.	
1	MEAND2	2	2	2	.	
1	MEAND3	3	3	3	.	
1	MEAND4	4	4	4	.	
1	MEAND5	5	5	5	.	
1	MEAND6	6	6	6	.	
1	MEAND7	7	7	7	.	
1	MEAND8	8	8	8	.	
1	MEAND9	9	9	9	.	
1	MEAND10	10	10	10	.	
Worker=21, Time Series=2						
N Obs	Variable	Minimum	Maximum	Mean	Std Dev	
1	MEAND1	1	1	1	.	
1	MEAND2	1.9	1.9	1.9	.	
1	MEAND3	2.95	2.95	2.95	.	
1	MEAND4	3.9	3.9	3.9	.	
1	MEAND5	4.8	4.8	4.8	.	
1	MEAND6	5.8	5.8	5.8	.	
1	MEAND7	6.85	6.85	6.85	.	
1	MEAND8	7.8	7.8	7.8	.	
1	MEAND9	8.95	8.95	8.95	.	
1	MEAND10	9.95	9.95	9.95	.	
Worker=21, Time Series=3						
N Obs	Variable	Minimum	Maximum	Mean	Std Dev	
1	MEAND1	1.25	1.25	1.25	.	
1	MEAND2	2.5	2.5	2.5	.	
1	MEAND3	3.65	3.65	3.65	.	
1	MEAND4	5.05	5.05	5.05	.	
1	MEAND5	6.3	6.3	6.3	.	
1	MEAND6	7.25	7.25	7.25	.	
1	MEAND7	8.55	8.55	8.55	.	
1	MEAND8	9.65	9.65	9.65	.	
1	MEAND9	11.1	11.1	11.1	.	
1	MEAND10	12.2	12.2	12.2	.	

Worker=21, Time Series=4						
N Obs	Variable	Minimum	Maximum	Mean	Std Dev	
1	MEAND1	1.9	1.9	1.9	.	
1	MEAND2	3.2	3.2	3.2	.	
1	MEAND3	5.25	5.25	5.25	.	
1	MEAND4	6.25	6.25	6.25	.	
1	MEAND5	8.55	8.55	8.55	.	
1	MEAND6	9.8	9.8	9.8	.	
1	MEAND7	11.5	11.5	11.5	.	
1	MEAND8	13.15	13.15	13.15	.	
1	MEAND9	15.4	15.4	15.4	.	
1	MEAND10	16.9	16.9	16.9	.	
Worker=22, Time Series=1						
N Obs	Variable	Minimum	Maximum	Mean	Std Dev	
1	MEAND1	1.65	1.65	1.65	.	
1	MEAND2	3.3	3.3	3.3	.	
1	MEAND3	5	5	5	.	
1	MEAND4	6.55	6.55	6.55	.	
1	MEAND5	8.6	8.6	8.6	.	
1	MEAND6	10.8	10.8	10.8	.	
1	MEAND7	13.1	13.1	13.1	.	
1	MEAND8	14.8	14.8	14.8	.	
1	MEAND9	16.6	16.6	16.6	.	
1	MEAND10	18.4	18.4	18.4	.	
Worker=22, Time Series=2						
N Obs	Variable	Minimum	Maximum	Mean	Std Dev	
1	MEAND1	1.75	1.75	1.75	.	
1	MEAND2	3.4	3.4	3.4	.	
1	MEAND3	4.9	4.9	4.9	.	
1	MEAND4	6.05	6.05	6.05	.	
1	MEAND5	7.3	7.3	7.3	.	
1	MEAND6	8.35	8.35	8.35	.	
1	MEAND7	10.45	10.45	10.45	.	
1	MEAND8	11.8	11.8	11.8	.	
1	MEAND9	13	13	13	.	
1	MEAND10	14.5	14.5	14.5	.	

Appendix A

Worker=23, Time Series=1						
N Obs	Variable	Minimum	Maximum	Mean	Std Dev	
1	MEAND1	1.25	1.25	1.25	.	
1	MEAND2	2.65	2.65	2.65	.	
1	MEAND3	3.7	3.7	3.7	.	
1	MEAND4	5.35	5.35	5.35	.	
1	MEAND5	6.3	6.3	6.3	.	
1	MEAND6	7.1	7.1	7.1	.	
1	MEAND7	8.55	8.55	8.55	.	
1	MEAND8	9.75	9.75	9.75	.	
1	MEAND9	10.95	10.95	10.95	.	
1	MEAND10	12.25	12.25	12.25	.	
Worker=23, Time Series=2						
N Obs	Variable	Minimum	Maximum	Mean	Std Dev	
1	MEAND1	1.45	1.45	1.45	.	
1	MEAND2	2.65	2.65	2.65	.	
1	MEAND3	4.25	4.25	4.25	.	
1	MEAND4	5.55	5.55	5.55	.	
1	MEAND5	6.85	6.85	6.85	.	
1	MEAND6	8.3	8.3	8.3	.	
1	MEAND7	9.55	9.55	9.55	.	
1	MEAND8	10.85	10.85	10.85	.	
1	MEAND9	12.25	12.25	12.25	.	
1	MEAND10	13.6	13.6	13.6	.	
Worker=23, Time Series=3						
N Obs	Variable	Minimum	Maximum	Mean	Std Dev	
1	MEAND1	1.4	1.4	1.4	.	
1	MEAND2	2.55	2.55	2.55	.	
1	MEAND3	4.15	4.15	4.15	.	
1	MEAND4	5.2	5.2	5.2	.	
1	MEAND5	6.45	6.45	6.45	.	
1	MEAND6	8.35	8.35	8.35	.	
1	MEAND7	9.5	9.5	9.5	.	
1	MEAND8	10.7	10.7	10.7	.	
1	MEAND9	11.75	11.75	11.75	.	
1	MEAND10	13.15	13.15	13.15	.	

Worker=23, Time Series=4						
N Obs	Variable	Minimum	Maximum	Mean	Std Dev	
1	MEAND1	1.5	1.5	1.5	.	
1	MEAND2	3.3	3.3	3.3	.	
1	MEAND3	4.75	4.75	4.75	.	
1	MEAND4	6.45	6.45	6.45	.	
1	MEAND5	7.55	7.55	7.55	.	
1	MEAND6	9.3	9.3	9.3	.	
1	MEAND7	11	11	11	.	
1	MEAND8	12.05	12.05	12.05	.	
1	MEAND9	14.25	14.25	14.25	.	
1	MEAND10	15.95	15.95	15.95	.	
Worker=23, Time Series=5						
N Obs	Variable	Minimum	Maximum	Mean	Std Dev	
1	MEAND1	1.65	1.65	1.65	.	
1	MEAND2	3.45	3.45	3.45	.	
1	MEAND3	5.4	5.4	5.4	.	
1	MEAND4	7.35	7.35	7.35	.	
1	MEAND5	9	9	9	.	
1	MEAND6	10.55	10.55	10.55	.	
1	MEAND7	12.3	12.3	12.3	.	
1	MEAND8	13.45	13.45	13.45	.	
1	MEAND9	15.5	15.5	15.5	.	
1	MEAND10	17.15	17.15	17.15	.	
Worker=24, Time Series=1						
N Obs	Variable	Minimum	Maximum	Mean	Std Dev	
1	MEAND1	1.35	1.35	1.35	.	
1	MEAND2	2.85	2.85	2.85	.	
1	MEAND3	4.1	4.1	4.1	.	
1	MEAND4	5.25	5.25	5.25	.	
1	MEAND5	6.75	6.75	6.75	.	
1	MEAND6	8.1	8.1	8.1	.	
1	MEAND7	9.4	9.4	9.4	.	
1	MEAND8	10.8	10.8	10.8	.	
1	MEAND9	12.2	12.2	12.2	.	
1	MEAND10	13.6	13.6	13.6	.	

Worker=24, Time Series=2						
N Obs	Variable	Minimum	Maximum	Mean	Std Dev	
1	MEAND1	1.15	1.15	1.15	.	
1	MEAND2	2.45	2.45	2.45	.	
1	MEAND3	4.2	4.2	4.2	.	
1	MEAND4	4.85	4.85	4.85	.	
1	MEAND5	6.55	6.55	6.55	.	
1	MEAND6	7.7	7.7	7.7	.	
1	MEAND7	8.95	8.95	8.95	.	
1	MEAND8	10	10	10	.	
1	MEAND9	11.3	11.3	11.3	.	
1	MEAND10	12.45	12.45	12.45	.	
Worker=24, Time Series=3						
N Obs	Variable	Minimum	Maximum	Mean	Std Dev	
1	MEAND1	1.35	1.35	1.35	.	
1	MEAND2	2.8	2.8	2.8	.	
1	MEAND3	4.25	4.25	4.25	.	
1	MEAND4	4.85	4.85	4.85	.	
1	MEAND5	6.55	6.55	6.55	.	
1	MEAND6	7.95	7.95	7.95	.	
1	MEAND7	9.35	9.35	9.35	.	
1	MEAND8	10.75	10.75	10.75	.	
1	MEAND9	11.65	11.65	11.65	.	
1	MEAND10	13.2	13.2	13.2	.	
Worker=24, Time Series=4						
N Obs	Variable	Minimum	Maximum	Mean	Std Dev	
1	MEAND1	1.95	1.95	1.95	.	
1	MEAND2	3.2	3.2	3.2	.	
1	MEAND3	4.65	4.65	4.65	.	
1	MEAND4	6.85	6.85	6.85	.	
1	MEAND5	8.8	8.8	8.8	.	
1	MEAND6	10.3	10.3	10.3	.	
1	MEAND7	12.2	12.2	12.2	.	
1	MEAND8	13.9	13.9	13.9	.	
1	MEAND9	15.6	15.6	15.6	.	
1	MEAND10	17.25	17.25	17.25	.	

Worker=24, Time Series=5						
N Obs	Variable	Minimum	Maximum	Mean	Std Dev	
1	MEAND1	1.95	1.95	1.95	.	
1	MEAND2	3.85	3.85	3.85	.	
1	MEAND3	5.1	5.1	5.1	.	
1	MEAND4	7.9	7.9	7.9	.	
1	MEAND5	9.9	9.9	9.9	.	
1	MEAND6	11.8	11.8	11.8	.	
1	MEAND7	14.15	14.15	14.15	.	
1	MEAND8	16.35	16.35	16.35	.	
1	MEAND9	18.45	18.45	18.45	.	
1	MEAND10	21.1	21.1	21.1	.	
Worker=24, Time Series=6						
N Obs	Variable	Minimum	Maximum	Mean	Std Dev	
1	MEAND1	2.35	2.35	2.35	.	
1	MEAND2	4.4	4.4	4.4	.	
1	MEAND3	5.9	5.9	5.9	.	
1	MEAND4	8.45	8.45	8.45	.	
1	MEAND5	9.95	9.95	9.95	.	
1	MEAND6	11.3	11.3	11.3	.	
1	MEAND7	13.3	13.3	13.3	.	
1	MEAND8	15.3	15.3	15.3	.	
1	MEAND9	17.45	17.45	17.45	.	
1	MEAND10	19.4	19.4	19.4	.	
Worker=25, Time Series=1						
N Obs	Variable	Minimum	Maximum	Mean	Std Dev	
1	MEAND1	1.4	1.4	1.4	.	
1	MEAND2	2.55	2.55	2.55	.	
1	MEAND3	3.95	3.95	3.95	.	
1	MEAND4	4.9	4.9	4.9	.	
1	MEAND5	6.35	6.35	6.35	.	
1	MEAND6	7.5	7.5	7.5	.	
1	MEAND7	8.45	8.45	8.45	.	
1	MEAND8	9.85	9.85	9.85	.	
1	MEAND9	10.85	10.85	10.85	.	
1	MEAND10	12	12	12	.	

Worker=25, Time Series=2						
N Obs	Variable	Minimum	Maximum	Mean	Std Dev	
1	MEAND1	1.5	1.5	1.5	.	
1	MEAND2	2.9	2.9	2.9	.	
1	MEAND3	4.15	4.15	4.15	.	
1	MEAND4	5.45	5.45	5.45	.	
1	MEAND5	7	7	7	.	
1	MEAND6	8.3	8.3	8.3	.	
1	MEAND7	9.9	9.9	9.9	.	
1	MEAND8	11.4	11.4	11.4	.	
1	MEAND9	12.65	12.65	12.65	.	
1	MEAND10	14.1	14.1	14.1	.	
Worker=26, Time Series=1						
N Obs	Variable	Minimum	Maximum	Mean	Std Dev	
1	MEAND1	1.3	1.3	1.3	.	
1	MEAND2	2.85	2.85	2.85	.	
1	MEAND3	4.4	4.4	4.4	.	
1	MEAND4	5.65	5.65	5.65	.	
1	MEAND5	7.55	7.55	7.55	.	
1	MEAND6	8.95	8.95	8.95	.	
1	MEAND7	10.4	10.4	10.4	.	
1	MEAND8	11.8	11.8	11.8	.	
1	MEAND9	13.25	13.25	13.25	.	
1	MEAND10	14.95	14.95	14.95	.	
Worker=26, Time Series=2						
N Obs	Variable	Minimum	Maximum	Mean	Std Dev	
1	MEAND1	1.45	1.45	1.45	.	
1	MEAND2	2.6	2.6	2.6	.	
1	MEAND3	3.6	3.6	3.6	.	
1	MEAND4	5.15	5.15	5.15	.	
1	MEAND5	6.2	6.2	6.2	.	
1	MEAND6	7.35	7.35	7.35	.	
1	MEAND7	8.7	8.7	8.7	.	
1	MEAND8	10.2	10.2	10.2	.	
1	MEAND9	11.5	11.5	11.5	.	
1	MEAND10	12.8	12.8	12.8	.	

Worker=26, Time Series=3						
N Obs	Variable	Minimum	Maximum	Mean	Std Dev	
1	MEAND1	1.9	1.9	1.9	.	
1	MEAND2	2.9	2.9	2.9	.	
1	MEAND3	5.1	5.1	5.1	.	
1	MEAND4	6.7	6.7	6.7	.	
1	MEAND5	8.35	8.35	8.35	.	
1	MEAND6	9.85	9.85	9.85	.	
1	MEAND7	11.55	11.55	11.55	.	
1	MEAND8	13.15	13.15	13.15	.	
1	MEAND9	14.85	14.85	14.85	.	
1	MEAND10	16.55	16.55	16.55	.	
Worker=26, Time Series=4						
N Obs	Variable	Minimum	Maximum	Mean	Std Dev	
1	MEAND1	1.2	1.2	1.2	.	
1	MEAND2	2.55	2.55	2.55	.	
1	MEAND3	3.6	3.6	3.6	.	
1	MEAND4	5.2	5.2	5.2	.	
1	MEAND5	6.65	6.65	6.65	.	
1	MEAND6	7.8	7.8	7.8	.	
1	MEAND7	9	9	9	.	
1	MEAND8	10.45	10.45	10.45	.	
1	MEAND9	11.75	11.75	11.75	.	
1	MEAND10	13.2	13.2	13.2	.	
Worker=26, Time Series=5						
N Obs	Variable	Minimum	Maximum	Mean	Std Dev	
1	MEAND1	1.7	1.7	1.7	.	
1	MEAND2	3.3	3.3	3.3	.	
1	MEAND3	5.55	5.55	5.55	.	
1	MEAND4	6.9	6.9	6.9	.	
1	MEAND5	8.75	8.75	8.75	.	
1	MEAND6	10.65	10.65	10.65	.	
1	MEAND7	12.05	12.05	12.05	.	
1	MEAND8	13.9	13.9	13.9	.	
1	MEAND9	15.6	15.6	15.6	.	
1	MEAND10	17.3	17.3	17.3	.	

Worker=26, Time Series=6						
N Obs	Variable	Minimum	Maximum	Mean	Std Dev	
1	MEAND1	1.75	1.75	1.75	.	
1	MEAND2	3.2	3.2	3.2	.	
1	MEAND3	4.35	4.35	4.35	.	
1	MEAND4	5.9	5.9	5.9	.	
1	MEAND5	7.4	7.4	7.4	.	
1	MEAND6	9.1	9.1	9.1	.	
1	MEAND7	10.45	10.45	10.45	.	
1	MEAND8	12.2	12.2	12.2	.	
1	MEAND9	13.4	13.4	13.4	.	
1	MEAND10	14.75	14.75	14.75	.	
Worker=27, Time Series=1						
N Obs	Variable	Minimum	Maximum	Mean	Std Dev	
1	MEAND1	1.55	1.55	1.55	.	
1	MEAND2	2.9	2.9	2.9	.	
1	MEAND3	4.25	4.25	4.25	.	
1	MEAND4	5.1	5.1	5.1	.	
1	MEAND5	6.6	6.6	6.6	.	
1	MEAND6	7.7	7.7	7.7	.	
1	MEAND7	9.3	9.3	9.3	.	
1	MEAND8	10.65	10.65	10.65	.	
1	MEAND9	12.25	12.25	12.25	.	
1	MEAND10	13.7	13.7	13.7	.	
Worker=27, Time Series=2						
N Obs	Variable	Minimum	Maximum	Mean	Std Dev	
1	MEAND1	1.5	1.5	1.5	.	
1	MEAND2	2.9	2.9	2.9	.	
1	MEAND3	5.35	5.35	5.35	.	
1	MEAND4	6.85	6.85	6.85	.	
1	MEAND5	9	9	9	.	
1	MEAND6	10.75	10.75	10.75	.	
1	MEAND7	12.25	12.25	12.25	.	
1	MEAND8	13.75	13.75	13.75	.	
1	MEAND9	15.7	15.7	15.7	.	
1	MEAND10	17.7	17.7	17.7	.	

Worker=27, Time Series=3						
N Obs	Variable	Minimum	Maximum	Mean	Std Dev	
1	MEAND1	1.15	1.15	1.15	.	
1	MEAND2	2.15	2.15	2.15	.	
1	MEAND3	3.15	3.15	3.15	.	
1	MEAND4	4	4	4	.	
1	MEAND5	5.15	5.15	5.15	.	
1	MEAND6	6.3	6.3	6.3	.	
1	MEAND7	7.3	7.3	7.3	.	
1	MEAND8	8.3	8.3	8.3	.	
1	MEAND9	9.45	9.45	9.45	.	
1	MEAND10	10.45	10.45	10.45	.	
Worker=27, Time Series=4						
N Obs	Variable	Minimum	Maximum	Mean	Std Dev	
1	MEAND1	1.2	1.2	1.2	.	
1	MEAND2	2.6	2.6	2.6	.	
1	MEAND3	3.75	3.75	3.75	.	
1	MEAND4	5.45	5.45	5.45	.	
1	MEAND5	6.6	6.6	6.6	.	
1	MEAND6	8	8	8	.	
1	MEAND7	9.35	9.35	9.35	.	
1	MEAND8	10.6	10.6	10.6	.	
1	MEAND9	12.05	12.05	12.05	.	
1	MEAND10	13.35	13.35	13.35	.	
Worker=27, Time Series=5						
N Obs	Variable	Minimum	Maximum	Mean	Std Dev	
1	MEAND1	1.65	1.65	1.65	.	
1	MEAND2	2.95	2.95	2.95	.	
1	MEAND3	4.1	4.1	4.1	.	
1	MEAND4	5.75	5.75	5.75	.	
1	MEAND5	7.2	7.2	7.2	.	
1	MEAND6	8.45	8.45	8.45	.	
1	MEAND7	10.25	10.25	10.25	.	
1	MEAND8	12.05	12.05	12.05	.	
1	MEAND9	13.25	13.25	13.25	.	
1	MEAND10	14.9	14.9	14.9	.	

Worker=28, Time Series=1						
N Obs	Variable	Minimum	Maximum	Mean	Std Dev	
1	MEAND1	1.2	1.2	1.2	.	
1	MEAND2	2.25	2.25	2.25	.	
1	MEAND3	3.75	3.75	3.75	.	
1	MEAND4	5.25	5.25	5.25	.	
1	MEAND5	6.25	6.25	6.25	.	
1	MEAND6	7.7	7.7	7.7	.	
1	MEAND7	8.95	8.95	8.95	.	
1	MEAND8	10.2	10.2	10.2	.	
1	MEAND9	11.55	11.55	11.55	.	
1	MEAND10	13	13	13	.	
Worker=28, Time Series=2						
N Obs	Variable	Minimum	Maximum	Mean	Std Dev	
1	MEAND1	1.45	1.45	1.45	.	
1	MEAND2	2.7	2.7	2.7	.	
1	MEAND3	3.75	3.75	3.75	.	
1	MEAND4	5.35	5.35	5.35	.	
1	MEAND5	6.85	6.85	6.85	.	
1	MEAND6	8.1	8.1	8.1	.	
1	MEAND7	9.45	9.45	9.45	.	
1	MEAND8	10.95	10.95	10.95	.	
1	MEAND9	12.5	12.5	12.5	.	
1	MEAND10	13.8	13.8	13.8	.	
Worker=28, Time Series=3						
N Obs	Variable	Minimum	Maximum	Mean	Std Dev	
1	MEAND1	1.25	1.25	1.25	.	
1	MEAND2	2.65	2.65	2.65	.	
1	MEAND3	3.75	3.75	3.75	.	
1	MEAND4	5.3	5.3	5.3	.	
1	MEAND5	6.5	6.5	6.5	.	
1	MEAND6	8.05	8.05	8.05	.	
1	MEAND7	9.5	9.5	9.5	.	
1	MEAND8	10.7	10.7	10.7	.	
1	MEAND9	11.85	11.85	11.85	.	
1	MEAND10	13.2	13.2	13.2	.	

Worker=28, Time Series=4						
N Obs	Variable	Minimum	Maximum	Mean	Std Dev	
1	MEAND1	1.35	1.35	1.35	.	
1	MEAND2	2.55	2.55	2.55	.	
1	MEAND3	4.05	4.05	4.05	.	
1	MEAND4	5.15	5.15	5.15	.	
1	MEAND5	6.55	6.55	6.55	.	
1	MEAND6	7.8	7.8	7.8	.	
1	MEAND7	9.2	9.2	9.2	.	
1	MEAND8	10.65	10.65	10.65	.	
1	MEAND9	11.85	11.85	11.85	.	
1	MEAND10	13.15	13.15	13.15	.	
Automobile-Manufacturing Plant						
Worker= 2, Time Series=1						
N Obs	Variable	Minimum	Maximum	Mean	Std Dev	
1	MEAND1	1.4	1.4	1.4	.	
1	MEAND2	3.25	3.25	3.25	.	
1	MEAND3	4.4	4.4	4.4	.	
1	MEAND4	6.05	6.05	6.05	.	
1	MEAND5	7.65	7.65	7.65	.	
1	MEAND6	9.15	9.15	9.15	.	
1	MEAND7	10.6	10.6	10.6	.	
1	MEAND8	12.05	12.05	12.05	.	
1	MEAND9	13.6	13.6	13.6	.	
1	MEAND10	15.1	15.1	15.1	.	
Worker=2, Time Series=2						
N Obs	Variable	Minimum	Maximum	Mean	Std Dev	
1	MEAND1	1.4	1.4	1.4	.	
1	MEAND2	2.95	2.95	2.95	.	
1	MEAND3	4.35	4.35	4.35	.	
1	MEAND4	6.2	6.2	6.2	.	
1	MEAND5	7.75	7.75	7.75	.	
1	MEAND6	9.45	9.45	9.45	.	
1	MEAND7	11.1	11.1	11.1	.	
1	MEAND8	13	13	13	.	
1	MEAND9	14.4	14.4	14.4	.	
1	MEAND10	16.05	16.05	16.05	.	

Worker=2, Time Series=3						
N Obs	Variable	Minimum	Maximum	Mean	Std Dev	
1	MEAND1	1.35	1.35	1.35	.	
1	MEAND2	2.85	2.85	2.85	.	
1	MEAND3	4.2	4.2	4.2	.	
1	MEAND4	5.65	5.65	5.65	.	
1	MEAND5	7.35	7.35	7.35	.	
1	MEAND6	8.85	8.85	8.85	.	
1	MEAND7	10.05	10.05	10.05	.	
1	MEAND8	11.65	11.65	11.65	.	
1	MEAND9	13	13	13	.	
1	MEAND10	14.45	14.45	14.45	.	
Worker=3, Time Series=1						
N Obs	Variable	Minimum	Maximum	Mean	Std Dev	
1	MEAND1	1.45	1.45	1.45	.	
1	MEAND2	2.6	2.6	2.6	.	
1	MEAND3	4.55	4.55	4.55	.	
1	MEAND4	5.85	5.85	5.85	.	
1	MEAND5	7.25	7.25	7.25	.	
1	MEAND6	8.8	8.8	8.8	.	
1	MEAND7	10.2	10.2	10.2	.	
1	MEAND8	11.55	11.55	11.55	.	
1	MEAND9	13.15	13.15	13.15	.	
1	MEAND10	14.7	14.7	14.7	.	
Worker=3, Time Series=2						
N Obs	Variable	Minimum	Maximum	Mean	Std Dev	
1	MEAND1	1.5	1.5	1.5	.	
1	MEAND2	3	3	3	.	
1	MEAND3	4.8	4.8	4.8	.	
1	MEAND4	6.3	6.3	6.3	.	
1	MEAND5	7.4	7.4	7.4	.	
1	MEAND6	9.3	9.3	9.3	.	
1	MEAND7	10.7	10.7	10.7	.	
1	MEAND8	12.1	12.1	12.1	.	
1	MEAND9	13.8	13.8	13.8	.	
1	MEAND10	15.4	15.4	15.4	.	

APPENDIX B

Results from the Analyses for all 148 Time Series

Appendix B

Data Set	Worker	Time Series	Significant Correlation Coefficients	Lag	Increasing Variance With Lag?	Stationarity Plot	Stationarity Test (no linear effect)	Stationarity Test (Diff. Data)	Significant Correlation Coefficients (Diff. Data)	Lag
Alkyl Lead Manufacturing Plant	1	1	0.382	8	No	S	S			
(alkyl Lead)	2	1			No	S	S			
	3	1			No	S	S			
	4	1			No	S	S			
Alkyl Lead Manufacturing Plant	1	1			No	S	S			
(Inorganic Lead)	2	1			No	S	S			
	3	1			No	S	S			
	4	1			No	S	S			
Pesticide-Production	1	1	-	-	Yes	NS	S			
Manufacturing Plant		2	0.385	5	No	S	S			
		3	0.480	1	Yes	NS	NS	S	-0.537	1
			0.451	2						
			0.457	4						
		4			No	S	S			
		5	0.391	1	No	NS	S			
			0.398	2						
			0.401	3						
		6	-	-	Yes	S	S			
		7	0.544	1	Yes	NS	NS	S	-0.409	1
			0.479	2						
			0.376	3						
		8	-0.398	4	No	S	S			
	2	1			No	S	S			
	3	1			No	S	S			
	4	1			No	S	S			

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Data Set	Worker	Time Series	Significant Correlation Coefficients	Lag	Increasing Variance With Lag?	Stationarity Plot	Stationarity Test (no linear effect)	Stationarity Test (Diff. Data)	Significant Correlation Coefficients (Diff. Data)	Lag
	5	1			No	S	S			
	6	1	0.397	1	Yes	NS	S			
		2			No	S	S			
		3	0.560	1	Yes	NS	NS	S	-	-
			0.419	2						
		4			No	S	S			
		5	-	-	Yes	S	S			
		6	-	-	Yes	S	S			
		7	0.457	1	Yes	S	S			
		8			No	S	S			
	7	1			No	S	S			
		2			No	S	S			
		3			No	S	S			
		4			No	S	S			
		5	0.481	3	No	NS	S			
		6			No	S	S			
		7	-	-	Yes	S	S			
		8			No	S	S			
		9	0.453	2	Yes	S	S			
	8	1			No	S	S			
	9	1			No	NS	S			
		2			No	S	S			
		3			No	S	S			
		4	0.385	2	No	NS	S			
		5			No	S	S			

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Data Set	Worker	Time Series	Significant Correlation Coefficients	Lag	Increasing Variance With Lag?	Stationarity Plot	Stationarity Test (no linear effect)	Stationarity Test (Diff. Data)	Significant Correlation Coefficients (Diff. Data)	Lag
		6			No	NS	S			
		7	0.502	1	Yes	NS	NS	S	-0.510	1
			0.459	2						
		8	0.476	1	Yes	S	NS	S		
			0.372	2						
	10	1			No	S	S			
		2			No	S	S			
		3			No	S	S			
		4			No	S	S			
		5			No	S	S			
		6			No	S	S			
		7	-0.375	5	No	S	S			
		8			No	S	S			
		9			No	S	S			
		10			No	S	S			
	11	1	0.368	3	Yes	NS	S			
		2			No	NS	S			
		3	0.386	1	Yes	NS	S			
		4	-	-	Yes	NS	S			
		5	0.464	1	No	S	S			
		6			No	S	S			
	12	1			No	S	S			
		2	0.448	2	Yes	S	S			
	13	1			No	S	S			
		2	0.496	1	No	NS	S			
		3			No	S	S			

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Data Set	Worker	Time Series	Significant Correlation Coefficients	Lag	Increasing Variance With Lag?	Stationarity Plot	Stationarity Test (no linear effect)	Stationarity Test (Diff. Data)	Significant Correlation Coefficients (Diff. Data)	Lag
		4	0.574	1	Yes	S	NS	S	-	-
		5	-	-	Yes	S	S			
	14	1	-	-	Yes	S	S			
	15	1	0.391	1	Yes	S	S			
			-0.422	6						
			-0.456	7						
		2			No	S	S			
		3	0.406	1	Yes	S	S			
		4	0.670	1	Yes	NS	NS	S	-	-
			0.444	2						
			0.387	3						
		5	-	-	Yes	S	S			
		6			No	S	S			
		7			No	S	S			
		8			No	NS	S			
		9			No	S	S			
		10	-	-	Yes	S	S			
		11	0.582	1	Yes	NS	NS	S	-	-
			0.432	2						
		12			No	S	S			
		13	0.382	1	Yes	S	S			
		14			No	S	S			
	16	1			No	S	S			
	17	1	0.432	1	No	NS	S			
		2	0.495	1	Yes	NS	S			
			0.629	2						

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Data Set	Worker	Time Series	Significant Correlation Coefficients	Lag	Increasing Variance With Lag?	Stationarity Plot	Stationarity Test (no linear effect)	Stationarity Test (Diff. Data)	Significant Correlation Coefficients (Diff. Data)	Lag
			0.604	3						
			0.411	4						
			0.404	6						
		3			No	S	S			
		4			No	S	S			
	18	1	0.463	1	No	NS	S			
		2			No	S	S			
	19	1	0.612	1	Yes	NS	S			
			0.622	2						
		2	0.393	4	No	S	S			
	20	1			No	S	S			
	21	1	-	-	Yes	S	S			
		2			No	S	S			
		3			No	NS	S			
		4			No	S	S			
	22	1			No	S	S			
		2			No	S	S			
	23	1			No	S	S			
		2	-0.421	2	No	S	S			
		3			No	S	S			
		4	-	-	Yes	S	S			
		5			No	S	S			
	24	1	0.401	1	Yes	S	NS	S	-	-

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Data Set	Worker	Time Series	Significant Correlation Coefficients	Lag	Increasing Variance With Lag?	Stationarity Plot	Stationarity Test (no linear effect)	Stationarity Test (Diff. Data)	Significant Correlation Coefficients (Diff. Data)	Lag
		2			No	S	S			
		3	0.438	2	No	S	S			
			0.438	4						
		4			No	S	S			
		5			No	S	S			
		6	0.375	1	No	S	S			
			0.429	4						
	25	1	-	-	Yes	S	S			
		2			No	S	S			
	26	1			No	S	S			
		2	0.509	1	Yes	NS	NS	S	-0.571	1
			0.434	2						
		3			No	S	S			
		4	-	-	Yes	S	S			
		5	0.579	1	Yes	NS	NS	S	-	-
			0.455	2						
			0.372	3						
		6	0.367	1	Yes	NS	S			
	27	1	0.451	1	Yes	S	S			
		2	0.701	1	Yes	NS	NS	S	-	-
			0.590	2						
			0.489	3						
			0.377	4						
		3			No	S	S			

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Data Set	Worker	Time Series	Significant Correlation Coefficients	Lag	Increasing Variance With Lag?	Stationarity Plot	Stationarity Test (no linear effect)	Stationarity Test (Diff. Data)	Significant Correlation Coefficients (Diff. Data)	Lag
		4			No	S	S			
		5	0.424	1	Yes	NS	S			
	28	1	0.428	1	No	S	S			
			-0.379	4						
		2	0.438	1	Yes	S	S			
		3	0.464	1	No	NS	NS	S	-	-
		4	0.428	1	Yes	NS	S			
			0.445	2						
Chloralkali-Processing Plant	1	1	0.492	1	No	S	S			
	2	1	0.362	1	Yes	S	S			
	3	1	-0.422	3	No	S	S			
	4	1			No	S	S			
	5	1	-0.331	7	No	S	S			
	6	1			No	S	S			
	7	1			No	S	S			
	8	1			No	S	S			
	9	1	0.333	5	No	S	S			
	10	1	-	-	Yes	S	S			

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Data Set	Worker	Time Series	Significant Correlation Coefficients	Lag	Increasing Variance With Lag?	Stationarity Plot	Stationarity Test (no linear effect)	Stationarity Test (Diff. Data)	Significant Correlation Coefficients (Diff. Data)	Lag
	11	1			No	S	S			
	12	1	0.413	1	No	S	S			
			-0.327	5						
			-0.317	6						
	13	1			No	S	S			
	14	1	0.404	4	No	S	S			
			0.353	5						
	15	1			No	S	S			
Automobile-Manufucturing Plant	1	1			No	S	S			
	2	1	0.654	1	Yes	NS	NS	S	-	-
			0.485	2						
			0.420	3						
		2			No	S	S			
		3	0.380	2	No	NS	S			
	3	1			No	S	S			
		2	0.384	1	No	NS	S			