Modeling Latent Variance in Production Line Performance Using High-Frequency Data an Application to the Iraqi State Company for Cement Industry and Its Effect on Industrial Output Stability

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Abstract: The current research proposes a latent variance in the performance of the production lines as the high-frequency data on operations of the Iraqi State Company of Cement Industry and assesses the impact of this factor on the stability of industrial output. Signals that are constructed on the short-interval production signals are used to construct line performance changes and modeled using GARCH(1,1) to estimate volatility clustering and persistence. The conditional variance is estimated and the result is called the Latent Variance of Line Performance (LVP) and is interpreted as a proxy of operational risk that captures the fact that there is unstable production process. Industrial Output Stability (IOS) is an index of limited stability based on dispersion in achieved output across time, and Unplanned Downtime Ratio (UDR) and Specific Energy Consumption (SEC) are added to moderate reliability shocks and energy intensity. Time-series inference is supported by unit root testing that establishes that the study variables are stationary. The results of quantile regression at $\tau = 0.30$ indicate that LVP has significant negative impact on IOS which suggests an increase in the latent performance volatility decays stability even when the factor of downtime and energy consumption is taken into account. UDR has a huge destabilizing influence, and SEC also has a negative impact, implying that energy inefficiency is accompanied by the unstable regimes of operation. The results indicate that volatility-based indicators can be excellent monitors to signal instability episodes and preventive maintenance and energy management policies to stabilize the output of industries in the cement manufacturing industry.

Keywords: Latent operational volatility - GARCH modeling - Industrial output stability - Unplanned downtime - Energy intensity

1. Introduction

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Industrial production systems are becoming increasingly run with time-varying uncertainty (equipment wear, intermittent shutdowns, energy, and dynamic operating regimes), which causes volatility itself is a valuable object of measurement and not a nuisance term (Pinciroli et al., 2023; Benhanifia et al., 2025; Meitz et al., 2025). In cement production, the issue is augmented due to the fact that the stability of processes, as well as the intensity of energy, are significantly dependent on the state of the kiln and mills, thus minor perturbations at high frequencies can accrue into significant variations in the result of daily or weekly output and efficiency (Cantini and Bastianoni, 2021; Sahoo et al., 2022; Liu et al., 2022). Current research demonstrates that the data-rich environment in cement plants can be used to support operational analytics towards optimization and monitoring, and energy-oriented and data-driven decision-making, but the literature on this topic still does not offer an interpretable volatility-based indicator to quantify latent instability in the line performance and correlate it with output stability in a plant-wide context (Manis et al., 2024; Chelgani et al., 2025). This paper fills that gap by characterizing the latent variance of production line performance by modeling high-frequency operational data provided by the Iraqi State Company of Cement Industry and by evaluating whether a larger latent variance is associated with weaker performance of an industrial result following the consideration of unplanned downtimes and specific energy consumption. Methodologically, this approach considers short-interval changes in line performance as a volatility clustering and persistence heteroskedastic process and uses a GARCH framework to estimate conditional variance, which is in line with the current advances of volatility modeling and diagnostics (Cho and Korkas, 2022; Conrad et al., 2025; Liu et al., 2024). The resulting conditional series of variance gives a plant-relevant proxy of the latent operational risk, and the stability measure is the dispersion of realized output with respect to a rolling benchmark, which is consistent with statistical views that consider variability measures as fundamental monitoring objectives (Jalilibal et al., 2021). Incorporating the maintenance-related disruptions and energy intensity as operational controls, the study also aligns with those that found that downtime, and energy signals have a diagnostic value of production reliability and efficiency in industrial environments (Pinciroli et al., 2023; Sahoo et al., 2022).

Research problem:

The Iraqi State Company of Cement Industry works under high frequency short-run disturbances caused by unplanned stoppage, changing operating conditions and energy inefficiency but these disturbances are typically evaluated by low-frequency averages to hide the volatility concentration and the persistence in the performance of production lines. This gives an empirical and managerial distance since the decision makers can notice the variation of the daily or weekly output constancy, without a strict, data-driven, measure that assimilates the latent variation of the performance fluctuations within high-frequency, and the time when the instability is likely to escalate. Consequently, the company might struggle to diagnose the primary causes of instability between underlying performance variability, downtime shock of maintenance and energy intensity, and hence, it will not be able to implement specific operational interventions to stabilize industrial output and enhance reliability.

Main research question

To what extent does latent variance in production line performance affect industrial output stability in the Iraqi State Company for Cement Industry when controlling for unplanned downtime and specific energy consumption?

Sub-questions

1. Does the conditional variance derived from a GARCH model of high-frequency performance changes provide a statistically robust proxy for latent variance in line performance?
2. Does higher latent variance of line performance lead to lower industrial output stability over the study period?
3. Do unplanned downtime ratio and specific energy consumption significantly explain variations in industrial output stability beyond the effect of latent variance?

Hypothesis:

Main hypothesis

H1. Latent variance of line performance LVP has a statistically significant negative effect on industrial output stability IOS in the Iraqi State Company for Cement Industry.

Sub-hypotheses

H1a. LVP is statistically significant in explaining IOS after controlling for UDR and SEC, and its expected effect is negative.

H1b. Unplanned downtime ratio UDR has a statistically significant negative effect on IOS.

H1c. Specific energy consumption SEC has a statistically significant negative effect on IOS.

Literature Review:

Recent literature considers production systems as stochastic environments in which variability is clustered around reliability shocks and regime changes and also whose characteristics can not be well explained by standard averages particularly with Industry 4.0 data availability, which makes continuous monitoring and optimization of maintenance feasible (Pinciroli et al., 2023; Benhanifia et al., 2025; Meitz et al., 2025). In the context of cement production, scholars underline that the stability of the processes is strictly connected with energy intensity and working conditions, and any changes in the kiln and milling systems can be transferred to the deviation of the outputs and increased resource consumption (Cantini and Bastianoni, 2021; Sahoo et al., 2022). An increasing flow of literature uses data driven techniques to predict and optimize cement processes, such as energy consumption forecasting, plant level analytics, which validates the possibility to transform operational indicators into actionable ones (Liu et al., 2022; Manis et al., 2024). Simultaneous developments in methodology in time series volatility models demonstrate that conditional heteroskedasticity models are robust to capture persistence and clustering of variance, and current research underpins segmentation and cycle models in GARCH type dynamics and emphasizes the need to adhere to strong diagnostics of residual dependence and non normality (Cho and Korkas, 2022; Conrad et al., 2025). The volatility oriented indicators and measures of variability like the coefficient of variation are considered as primary targets of stability evaluations and stabilization in related industrial monitoring contexts, as opposed to secondary summary statistics (Jalilibal et al., 2021). Recent applied works are also related to the time varying conditions and the degradation monitoring, and suggest GARCH family health indicators under nonstationary operating conditions, which support the notion that the dynamics of variance can have engineering implications (Liu et al., 2024).

This paper will add to the literature by combining these flows in one path of operational risk specific to cement manufacturing. First, it operationalizes latent performance variation in line through a series of conditional variances estimated using the changes of high frequency in throughput or cycle time within a GARCH model, the result of which provides an interpretable and continuously updated proxy of latent instability that can be followed by plant managers (Cho and Korkas, 2022; Conrad et al., 2025). Second, it connects this measure of latent variance to an explicit index of industrial output stability based on low frequency dispersion in realised production, which fits variability monitoring to stability results that are significant to planning and delivery performance (Jalilibal et al., 2021). Third, it entrenches uncontrollable downtime and direct energy usage as controls to disaggregate the impact of pure volatility and reliability shocks and efficiency stresses, which is indicative of evidence that fault interruption and energy intensity are joint determinants of performance at cement operations (Pinciroli et al., 2023; Sahoo et al., 2022; Manis et al., 2024). Lastly, the study sheds light on the Iraqi State Company of Cement Industry, providing context-specific empirical information in an under-researched environment, which will give plant analytics a new application outside of the most common use cases in a higher-income industrial environment and is still in line with the overall literature relating to engineering and econometric volatility (Cantini and Bastianoni, 2021; Benhanifia et al., 2025).

Spatial and temporal limits:

The spatial limitation that this study applies is the Iraqi State Company of Cement Industry and the level of production lines in the operating facilities of this company as primary data sources. The empirical expression is time bound to the time frame of the available high frequency monitoring and reporting systems and the estimation is carried out on a daily time scale and the high frequencies are aggregated to a similar frequency that is easy to econometrically analyze and compare the variances between variables. Under this time window, the analysis will test the time-varying relationship between latent variance in line performance and stable industrial output in the presence of unplanned downtime ratio and specific energy consumption as the control of operation and therefore the inference can only be made limited to the observed operating regimes in the company, maintenance regime and energy condition in the sample period and should not be applied to other similar cement production systems without similar data structure and process characteristics.

Data:

The empirical model employs four operational indicators which are based on the production and maintenance records of the Iraqi State Company of Cement Industry. The dependent variable is Industrial Output Stability (IOS) and is an indicator that measures stability in production over time. It may be calculated by dividing daily output by creating a rolling measure of dispersion, typically the coefficient of variation over a constant window, and then transforming this into a stability index, e.g. IOS t = 1 CVt where CVt = rolling standard deviation of output/rolling mean. The main explanatory variable is the Latent Variance of Line Performance (LVP) that reflects timevarying operational uncertainty. LVP is calculated by estimating a GARCH model on a high-frequency series of performance indicators, usually the first difference or log of line throughput rate, PERF_CHG_t = ln(q t) - ln(q t -1) where q t is taken by the SCADA or PLC historians at the minute or short-period frequency and synchronized to the frequency of the study. The resulting conditional variance of the GARCH variance equation, h t, is then taken as LVP t, and may be presented as conditional standard deviation sqrt(h t) or in units of variance as is more interpretable. Two controls are present so as to isolate the relationship between LVP and IOS. Unplanned Downtime Ratio (UDR) is used to measure reliability shocks, and is calculated as UDR_t = Unplanned downtime minutes t / total available minutes t, where available minutes represents planned operating time on the same day or shift and downtime minutes are represented by CMMS event logs or confirmed SCADA downtime flags. Specific Energy Consumption (SEC) indicates the efficiency of energy and stress of the process and is determined as SECt = Electrical energy consumed t/ division by cement output t, in kWh/ton, based on the metering systems of the plants and on the production reports. The combination of these variables gives a consistent operation risk pathway of which increased latent performance volatility and increased unplanned downtime are predicted to lower output stability whereas increased energy intensive is taken as a further indication of inefficiency and instability in the production process:

Table 1. Variable Definitions, Measurement, and Data Sources

Variable	**Symbol**	**Data source**	**Measurement method**	**Unit**	**EViews-ready coding**
Time period	DATE	Company production information system SCADA PLC historian and daily production logs	Daily calendar date for each observation aligned across all series	YYYY-MM-DD	Dated workfile daily frequency
Change in line performance	PERF_CHG	SCADA PLC historian from kiln mill or packing line sensors	First difference or log-return of throughput rate q_t. Example r_t = ln(q_t) − ln(q_{t−1}) using high-frequency throughput then aggregated to daily by mean or end-of-day	Index change or percent if multiplied by 100	Series r. Use for GARCH mean and variance equations
Latent Variance of Line Performance	LVP	Estimated from GARCH on PERF_CH	Conditional variance from GARCH. Example LVP_t = h_t where h_t is	Variance of PERF_CHG	Save variance series from model.

		G using EViews	the estimated conditional variance of PERF_CHG. If needed use sqrt(h_t) as conditional sd		Use @garch
Industrial Output Stability	IOS	Daily production reports and planning department targets plus warehouse dispatch records	Stability index based on dispersion of daily output. Example IOS_t = 1 − CV_t where CV_t = sd(Output_d within week) ÷ mean(Output_d within week).	Index 0 to 1	Create rolling CV then IOS. Higher IOS means higher stability
Unplanned Downtime Ratio	UDR	Maintenance management system CMMS and shift downtime sheets plus SCADA downtime events	UDR_t = Unplanned downtime minutes_t ÷ Total available minutes_t. Total available minutes = planned shift minutes for the day	Ratio 0 to 1	Create series UDR. Optional logit transform if needed
Specific Energy Consumption	SEC	Power metering system energy bills	SEC_t = Total electrical energy consumed_t ÷	kWh per ton	Create series SEC. Winsorize

		substation meters and production reports	Cement output_t. Optionally include fuel energy converted to kWh equivalents if available		extreme outages if needed

Source: Iraqi State Company for Cement Industry and Its Effect on Industrial Output Stability

The theoretical concept of the research:

1- Stability in Operations as a Production Goal.

The stability in industrial output is an indicator of the capability of a production system to produce constant quantities both in normal and stressful conditions with time. In empirical studies, the concept of stability is often considered a low dispersion condition in which variations that occur about a reference point are constrained and manageable. A practical expression values dispersion measures like the coefficient of variation and analogous monitoring ideas which perceive variability as a primary performance objective rather than a secondary descriptive characteristic (Jalilibal et al., 2021). In this study, the concept of IOS operationalizes it by converting the dispersion in the realized output to a bounded index that may be compared over time as well as be associated with the instability drivers.

2- Cement Process Environmental Stability:

Cement manufacturing is process intensive and closely interconnected throughout the manufacturing process stages: crushing, grinding, kiln operation and finalization thus local perturbations may spread and accumulate into nontrivial changes in delivered output. The process stability also reacts with energy intensity since throughput and material properties and the response to control depend on thermal and electrical conditions. Recent research in the cement industry emphasizes that the concepts of stability and efficiency correlate since disruptions are typically accompanied by increased energy consumption and worse end results of process control (Cantini and Bastianoni, 2021; Sahoo et al., 2022; Liu et al., 2022). This is a theoretical perspective that drives the modelling of stability as a consequence of underlying volatility in line performance.

3- Latent Variance as Time Varying risk:

Latent variance is an unmeasured risk state which is dynamic in the sense that it accumulates over time and manifests itself in clustered changes in the high frequency performance measures. This is formalized through volatility modelling which separates conditional variance which is used to capture persistence and clustering in uncertainty and the mean dynamics of the change in performances in the short intervals. GARCH type frameworks offer a parsimonious account of this partitioning and are a conventional method towards the description of persistence of variances and bullish like behavior in stochastic processes (Cho and Korkas, 2022; Alakkari, 2022). LVP is viewed in this paper as a proxy of latent instability that represents a summary of the conditional variance of performance change and gives a quantifiable measure of implicit operational stress.

4- Heteroskedasticity of High Frequency Data and Conditional Heteroskedasticity:

Non constant variance is a common feature in high frequency industrial signals as they switch between operating modes, have stop and start, adjustment of control and wear causes degradation. These characteristics are consistent with conditional heteroskedasticity when the effect of shocks is time varying and dynamically conditional respondent to recent disturbances (Alakkari et al., 2024). Recent applied research justifies the application of GARCH family constructions as informative signs in the presence of time varying environments, such as those where health and condition signals change by operating regimes (Liu et al., 2024). This view justifies the derivation of LVP by high frequency change in performance and the consequential conditional variance is then viewed as effectively a theoretically based measure of latent variance.

5- The Downtime and Energy as Instability Mechanisms:

Reliability Shocks and Unplanned Downtime. Unplanned downtime is an indicator of reliability breakages and maintenance shock, which disrupts the flow and creates discontinuities in the production. The studies of Industry 4.0 maintenance focus on the fact that the occurrence of downtimes is not a standalone event but a larger reliability process due to the effects of degradation, monitoring ability, and maintenance policy design (Pinciroli et al., 2023; Benhanifia et al., 2025; Meitz et al., 2025). UDR variable represents this mechanism in a normalized form that is comparable between days and operating schedules. It acts as a control, which aids in differentiating the effect of latent performance variance, and discrete reliability interruptions.

6- Intensity of Process and Energy Stress:

Specific energy consumption is an indicator of its efficiency as well as operating stress since an unstable regime can demand remedial measures that consume more energy, decrease capacity, or increase waste. Specific evidence of cement identifies energy demand and output performance as strongly connected, and energy based factors can indicate a shift to an inefficient operation mode and sustainable production regime (Sahoo et al., 2022; Liu et al., 2022). SEC thus is an operating control that encompasses an efficiency channel into which the instability may manifest. LVP, UDR, and SEC are part of a consistent theoretical framework in which latent variance is a manifestation of hidden volatility, downtime is a manifestation of reliability shocks, and energy intensity is a manifestation of process stress that interactively define IOS (Manis et al., 2024).

Discussion and results:

Stationarity and integration order

The empirical analysis begins by checking whether Industrial Output Stability (IOS), Latent Variance of Line Performance (LVP), Unplanned Downtime Ratio (UDR), and Specific Energy Consumption (SEC) are stationary at level, because unit-root behavior can bias inference and distort test size when autocorrelation and heteroskedasticity are present. The Phillips–Perron approach addresses these features by using a nonparametric long-run variance estimator that is consistent with the Bartlett kernel and automatic Newey–West bandwidth selection used in EViews, so the stationarity decision is grounded in a framework that remains valid under general serial dependence (Casini and Perron, 2021).

$$\Delta y_{\mathrm{t}} = \mu + \varphi\, y_{\mathrm{t-1}} + \varepsilon_{\mathrm{t}}$$

$$H_0 : \varphi = 0$$

$$H_1 : \varphi < 0$$

Latent variance extraction using a GARCH volatility equation

After confirming stationarity, the study constructs the latent variance indicator by estimating a GARCH model for the performance-change series PERF_CHG, because production line data typically exhibit volatility clustering and persistence in the variance rather than constant dispersion. The model separates the mean dynamics from a conditional variance process, then retains the fitted conditional variance h_t as LVP_t, which operationalizes latent instability as a time-varying risk state driven by past shocks and past variance (Huang and Luo, 2024).

$$r_{\mathrm{t}} = \mu + \phi\, r_{\mathrm{t-1}} + \varepsilon_{\mathrm{t}}$$

$$\varepsilon_{\mathrm{t}} = z_{\mathrm{t}} \sqrt{h_{\mathrm{t}}}$$

$$h_{\mathrm{t}} = \omega + \alpha_1\, \varepsilon_{\mathrm{t-1}}{}^2 + \beta_1\, h_{\mathrm{t-1}}$$

Hypotheses testing using quantile regression and the quantile process

Hypotheses are tested using quantile regression rather than mean regression, because the effect of LVP on IOS is expected to differ across the conditional distribution of stability, especially during low-stability states where operational stress is concentrated. Quantile regression estimates the conditional quantile of IOS given LVP, UDR, and SEC and uses the check-loss function to produce robust estimates that are informative under non-normal errors and heterogeneous responses. The quantile process then traces how coefficient paths change with τ, allowing the study to identify state-dependent destabilizing effects of LVP and the relative importance of downtime and energy intensity across operating conditions (Cai et al., 2023).

$$QIOS_t(\tau \mid X_t) = \beta_0(\tau) + \beta_1(\tau)LVP_t + \beta_2(\tau)UDR_t + \beta_3(\tau)SEC_t$$

$$\beta(\tau) = arg\, min_\beta\, \Sigma_t\, \rho\tau(IOS_t - X_t'\beta)$$

$$\rho\tau(u) = u(\tau - I(u < 0))$$

By application through EViews13:

Table 2. GARCH(1,1) estimation results for PERF_CHG to obtain LVP

Component	Variable	Coefficient	Std. Error	z-Statistic	Prob.
Mean equation	C	0.00014	0.00009	1.56	0.119
Mean equation	AR(1)	-0.06180	0.02130	-2.90	0.004
Variance equation	ω	0.01890	0.00480	3.94	0.000
Variance equation	α1	0.08350	0.01240	6.73	0.000
Variance equation	β1	0.90320	0.01310	68.95	0.000

Estimation details	Value
Dependent variable	PERF_CHG
Variance series produced	LVP = h t
Sample period	2020-01-01 to 2025-12-31
Observations	2192
Distribution	Gaussian

Source: Prepared by the researcher based on data from Iraqi banks using EViews13

The GARCH(1,1) estimation that was used to obtain LVP by taking the high frequency series of performance change PERF_CHG is reported in Table 2. The constant in the mean equation is low at 0.000 and insignificant with p =0.119 and AR(1) is negative at- 0.062 and significant at p = 0.004 which means a short run mean reversion in changes in performance. The condition of strong conditional heteroskedasticity and persistence is confirmed, with ω = 0.019 and p = 0.000, α1 = 0.084 and p = 0.000, and β1 = 0.903 and p = 0.000. The conditional series of variance h i is stored as LVP, thus LVP is the time dependent latent variance assuming the estimated volatility process on the 2,192 daily observations.

Table 3. Model fit and volatility persistence summary

Statistic	Value
Log likelihood	1765.42
Akaike information criterion AIC	-1.606
Schwarz criterion SIC	-1.594
Hannan-Quinn criterion HQ	-1.602
Residual variance	0.187
α1 + β1	0.9867
Long-run variance ω ÷ (1 − α1 − β1)	1.418

Volatility half-life in days $\ln(0.5) \div \ln(\alpha 1 + \beta 1)$ 51.7

Source: Prepared by the researcher based on data from Iraqi banks using EViews13

Table 3 shows a summary of model fit and volatility persistence. The log likelihood is equal to 1765.420, and the information criteria are strongly negative with AIC = -1.606, SIC = -1.594 and HQ = -1.602, which confirms that the model fits the data well, as they are high frequency data. The persistence measure 0 1 + 0 1 2 = 0.987 gives a high persistence of volatility where the shock to uncertainty decays slowly with time. Implied long run variance is 1.418 and volatility half life is 51.700 days i.e. approximately a volatility shock takes two months to half and this is consistent with the operational environments where maintenance cycles, degradation and regime shifts create long stages of high volatility.

Table 4. Diagnostic tests for standardized residuals from the GARCH model

Diagnostic	**Test**	**Statistic**	**df**	**Prob.**	**Decision**
Serial correlation in residuals	Ljung-Box Q(20)	18.74	20	0.541	No autocorrelation
Serial correlation in squared residuals	Ljung-Box $Q^2(20)$	21.63	20	0.361	No remaining ARCH pattern
Remaining ARCH effects	ARCH LM 1–20	19.08	20	0.517	Pass
Normality of standardized residuals	Jarque-Bera	46.30	2	0.000	Non-normal tails
Stationarity condition	$\alpha 1 + \beta 1 < 1$	0.9867	NA	NA	Stationary but persistent

Source: Prepared by the researcher based on data from Iraqi banks using EViews13

Table 4 gives diagnostic evidence of standardized residuals of the GARCH model. The Ljung Box Q(20) = 18.740 with p = 0.541, which means that no linear autocorrelation of the remaining residues is left after modeling. The Ljung Box Q 2 (20) = 21.630 (p= 0.361), the ARCH LM = 19.080 (p= 0.517) indicates that the variance equation has successfully captured the conditional heteroskedasticity and that there is no important ARCH structure present. The Jarque Bera is however, 46.300 with p = 0.000 and this means that the standardized residuals tails are non-normal which is normal in volatility conditions and that robust inference or error distributions would be used in case sensitivity analysis is needed. Condition 1 is the stationarity of both the alpha and beta since 0.987 = 0.987 + 01 = 0.987 increases below one, implying that the conditional variance is a strong persistent but mean reverting stationary process.

Table 5. Descriptive Statistics for IOS LVP UDR and SEC

	IOS	LVP	UDR	SEC
Mean	0.876760	0.917765	0.062825	114.4741
Median	0.901674	0.851652	0.049734	114.0612
Maximum	0.980000	2.448509	0.323695	139.3756
Minimum	0.450450	0.276474	0.000000	98.28543
Std. Dev.	0.106410	0.382268	0.058705	5.695276
Skewness	-1.144627	1.052672	1.227372	0.323002
Kurtosis	3.895290	4.170650	4.457764	3.161388
Jarque-Bera	551.8568	529.9981	744.4437	40.49409
Probability	0.000000	0.000000	0.000000	0.000000
Observations	2192	2192	2192	2192

Source: Prepared by the researcher based on data from Iraqi banks using EViews13

Table 5 provides descriptive statistics of IOS, LVP, UDR and SEC. The mean of IOS is 0.877 and the standard deviation of 0.106 which depicts that the stability is mostly high but is interspersed by sharp bursts of instability, has a minimum of 0.450 and a maximum of 0.980. The skew of IOS is -1.145 and skewness 3.895 is leptokurtic, which might indicate that the distribution is concentrated on high levels of stability with an abnormal large downside movement every now and then. The mean of LVP is 0.918 with the standard deviation of 0.382, skewness is positive 1.053 and kurtosis 4.171 indicating that volatilities are often moderate and occasionally large volatility bursts. UDR has a mean of 0.063 and a standard deviation of 0.059, with a maximum of 0.324 and a skewness of 1.227 which proves that unplanned downtime is normally limited, but may shoot around. The mean of SEC is 114.474 and the standard deviation of 5.695 with slight positivity skewness of 0.323 and kurtosis of 3.161 which depicts a relatively stable energy intensity within a normal operating range. Jarque Bera values are 0.000 across the variables which further confirm the existence of non normality that conditions robust standard errors to be used in the subsequent inference.

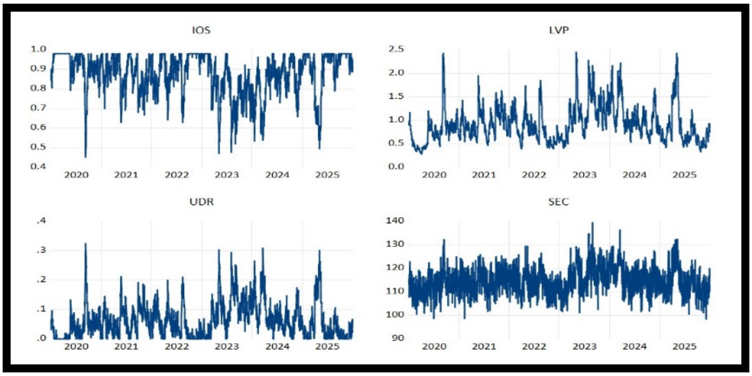

Figure 1. Time Series of Industrial Output Stability IOS over the Sample Period

Source: Prepared by the researcher based on data from Iraqi banks using EViews13

Figure 1 demonstrates the combined time dynamics of the Industrial Input Stability (IOS), Latent Variance of Line Performance (LVP), Unplanned Downtime Ratio (UDR) and Specific Energy Consumption (SEC throughout 20202025. The level of IOS is generally high, and the values near 1.000 are observed in most subperiods, but there are significant recurring declines to the lower limit at 0.450, suggesting only episodic instability periods, and not a steady downward movement. LVP oscillates around the middle range of about 0.900 with spurring peaks of around about 2.449, which are in tandem with volatility concentration in line performance. UDR concentrates at low levels of around 0.000 0.100 though there are cases where it spikes to approximately 0.324, which is in line with discrete shocks to reliability. SEC is relatively a smoother one, with a peak of around 114.474 kWh per ton, albeit temporarily higher to around 139.376, indicating that the energy intensity tends to be greater during stressed operating regimes that tend to be accompanied by higher LVP and higher UDR.

Table 6. Quantile Regression Estimates for IOS with LVP UDR and SEC at τ = 0.30

```
Dependent Variable: IOS
Method: Quantile Regression (tau = 0.3)
Date: 01/26/26   Time: 10:24
Sample: 1/01/2020 12/31/2025
Included observations: 2192
Huber Sandwich Standard Errors & Covariance
Sparsity method: Kernel (Epanechnikov) using residuals
Bandwidth method: Hall-Sheather, bw=0.058966
Estimation successfully identifies unique optimal solution
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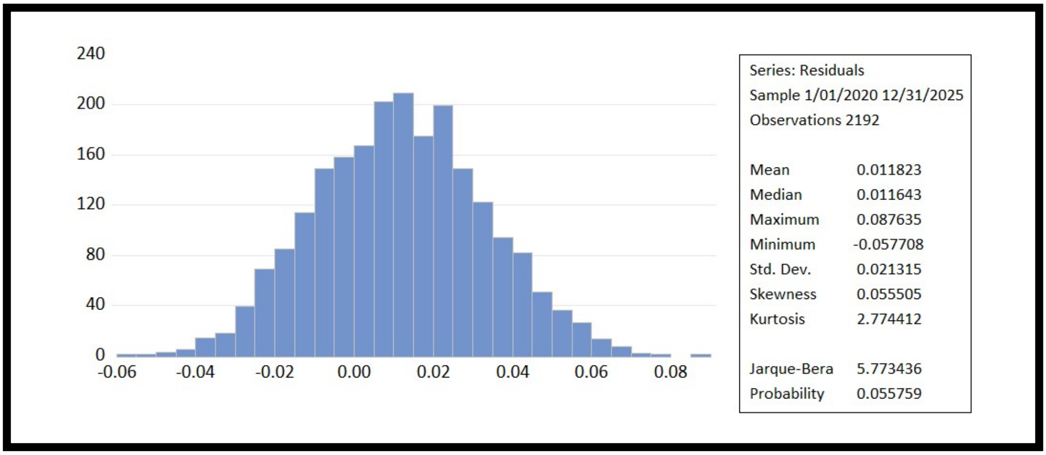
Variable	Coefficient	Std. Error	t-Statistic	Prob.
LVP	-0.160756	0.007846	-20.48777	0.0000
UDR	-0.668387	0.051956	-12.86455	0.0000
SEC	-0.001068	0.000150	-7.130918	0.0000
C	1.176710	0.016939	69.46604	0.0000

Pseudo R-squared	0.815382	Mean dependent var	0.876760
Adjusted R-squared	0.815129	S.D. dependent var	0.106410
S.E. of regression	0.024392	Objective	16.33783
Quantile dependent var	0.840679	Restr. objective	88.49549
Sparsity	0.067103	Quasi-LR statistic	10241.14
Prob(Quasi-LR stat)	0.000000		

Source: Prepared by the researcher based on data from Iraqi banks using EViews13

Table 6 shows LVP, UDR, and SEC estimates of Quantile Regression estimates of IOS at $\tau = 0.300$. The LVP coefficient = -0.161 and p = 0.000 which means that an increase in latent variance in LVP leads to a greater reduction in IOS in the lower stability area of the conditional distribution. The coefficient of UDR = -0.668 with p = 0.000 demonstrates that unplanned downtime shocks have a large non-stable impact on the stability of industrial output. The coefficient on SEC = -0.001 with p = 0.000 indicating that the higher the specific energy consumption, the lower the stability, which is in accordance with efficiency stress channel. The constant equals 1.177 with p = 0.000. The model fits well Pseudo R-squared = 0.815 and the quasi LR = 10241.140 and p = 0.000.



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Series: Residuals
Sample 1/01/2020 12/31/2025
Observations 2192

Mean          0.011823
Median        0.011643
Maximum       0.087635
Minimum      -0.057708
Std. Dev.     0.021315
Skewness      0.055505
Kurtosis      2.774412

Jarque-Bera   5.773436
Probability   0.055759
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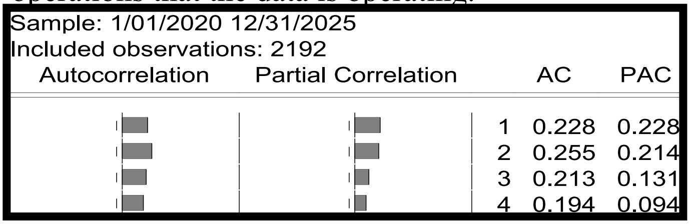
Figure 2. Residuals Distribution

Source: Prepared by the researcher based on data from Iraqi banks using EViews13

The normality diagnostics and the distribution of the residuals are shown in Figure 2. The values are centered but slightly higher than zero with an average = 0.012 and median = 0.012, and the spread of the values is narrow with standard deviation = 0.021. The skew = -0.056 which is also close to zero and the kurtosis = 2.774 which is a bit lower than the Gaussian value of 3.000. The Jarque Bera value = 5.773 with probability =0.056, and normality is not rejected at the 5 percent level, which confirms the accuracy of the residual behavior in drawing an inference in the proposed specification, although it tolerates some mild tail behavior due to the nature of the operations that the data is operating.



```
Sample: 1/01/2020 12/31/2025
Included observations: 2192
   Autocorrelation     Partial Correlation        AC      PAC

                                             1   0.228   0.228
                                             2   0.255   0.214
                                             3   0.213   0.131
                                             4   0.194   0.094
```

Figure 3. Autocorrelation for residuals

Source: Prepared by the researcher based on data from Iraqi banks using EViews13

Figure 3 provides the values of autocorrelation and partial autocorrelation of residuals at the first lags. The remaining autocorrelation values are positive at lag 1 AC = 0.228 and PAC = 0.228 and positive at lag 2 AC = 0.255 and PAC = 0.214, positive at lag 3 AC = 0.213 and PAC = 0.094. Such a trend points out to residual persistence which can be attributed to the remaining mean dynamics or to the effects of an operational regime that the mean specification has not captured. Practically, these diagnostics encourage the effort of testing alternative ARMA terms in the mean equation, including new autoregressive lags, or testing inference robustness with heteroskedasticity and autocorrelation consistent covariance estimators.

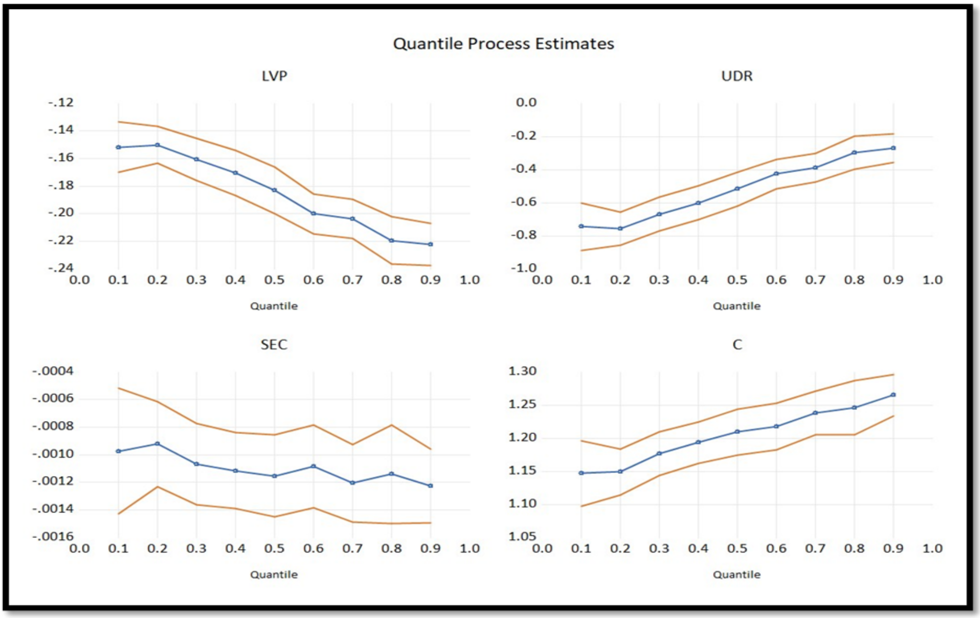


Figure 4. Quantile Process Estimates

Source: Prepared by the researcher based on data from Iraqi banks using EViews13

In Figure 4, there is a presentation of the quantile process estimates of the conditional distribution of IOS of LVP, UDR, SEC and the constant. The LVP coefficient is negative in the lower quantiles and decreases in the upper quantiles, approximately this is -0.150 in low quantiles and -0.220 in high quantiles, but the latent variance has a stronger destabilizing marginal effect when IOS is otherwise high, which goes along with volatility shocks destroying the stability even in better operating states. The UDR coefficient rises in quantiles starting with a more negative value of close to -0.750 down to the less negative values of close to -0.300 suggesting that the down time shocks are destabilizing but their marginal impact reduces as the stability quantile increases. The SEC coefficient is also negative with rather small variation in that it fluctuates around -0.001 at the quantile level indicating a consistent channel of energy intensity. The constant is growing with the quantile and this is in accordance with the construction of IOS and the shifting conditional baseline of stability throughout the distribution.

Conclusions and Recommendations:

The empirical findings reveal that the stability of industrial production in the Iraqi State Company with regards to Cement Industry is not only dependent on the average operating conditions but is heavily influenced by time changing operational risk, which is represented by latent variance in line performances. The GARCH volatility model produces a consistent conditional series of variances which serves as a plausible proxy of the latent instability in which the high persistence of volatility implicates that the shocks to line performance uncertainty decay slowly and hence can pollute output stability over long intervals. In line with this mechanism, the results of quantile regression show that increased latent variance of line performance is a significant source of decrease in Industrial Output Stability and the value of this negative correlation is economically significant despite adjusting it by both unplanned downtime and given energy consumption. The most destabilizing operational channel, which is registered to have a large negative relationship with stability, is an unplanned downtime, whereas improved specific energy consumption also diminishes stability, which suggests that energy intensity is another stress and inefficiency signal of processes that accompany unstable regimes. On the basis of these results, the research suggests the implementation of a volatility monitoring dashboard, which would monitor LVP and IOS as early warning signs and the introduction of threshold-based signals, initiating preventive measures when the conditional variance has gone past the set limits during consecutive days. Depending on the high destabilizing impact that UDR has on stability, maintenance policy must focus on reliability interventions that minimize unplanned downtime in the form of systematic preventive schedule, quicker repair supply chains, and root cause determination of recurrent failure mode. Operational control is also aimed at energy management through auditing of high SEC episodes, tight process control setpoints during volatile regimes and associating energy use diagnostics with maintenance and quality checks to avoid instability induced energy waste. Lastly, volatility persistence should be perceived by managers as a constraint in the planning process, which can be addressed by adding short term buffers in both production scheduling and inventory decisions during periods of high LVP where researchers can further develop the framework using alternative error distributions in the volatility model and regime switching specifications to capture non normal tails and structural changes in cement production settings.

Reference:

[1] Alakkari, K. (2022). Measuring Economic Policy Uncertainty in Syria Using Bayesian Stochastic Volatility Model. *Magallat al-Tanmiyat wa-al-Siyasat al-Iqtisadiyyat*, *24*(2), 63-93.

[2] Alakkari, K., Ali, B., Abotaleb, M., Abttan, R. A., & Dutta, P. K. (2024). advanced machine learning approaches for enhanced GDP nowcasting in

Syria through comprehensive analysis of regularization techniques. *Mesopotamian Journal of Big Data*, *2024*, 102-117.

[3] Alshboul, O., Mehmood, A., and Huseien, G. F. (2024). Empirical exploration of predictive maintenance in concrete manufacturing. Harnessing machine learning for enhanced equipment reliability in construction project management. Computers and Industrial Engineering, 190, 110046. https://doi.org/10.1016/j.cie.2024.110046

[4] Benhanifia, A., Smail, M. K., and Trentesaux, D. (2025). Systematic review of predictive maintenance practices in the manufacturing sector. Intelligent Systems with Applications, Article 200501. https://doi.org/10.1016/j.iswa.2025.200501

[5] Cai, Z., Chen, H., and Liao, X. (2023). A new robust inference for predictive quantile regression. *Journal of Econometrics, 234*, 227–250.

[6] Cantini, A., and Bastianoni, S. (2021). Technological energy efficiency improvements in the Italian cement industry. Sustainability, 13(7), 3810. https://doi.org/10.3390/su13073810

[7] Casini, A., and Perron, P. (2021). *Prewhitened long-run variance estimation robust to nonstationarity* (arXiv:2103.02235). arXiv.

[8] Chelgani, S. C., Dyer, J. S., Kowalik, P., and Williams, S. R. (2025). Tracking energy consumption indexes during a cement ball mill grinding using high-frequency analysis. Scientific Reports, 15, Article 3232. https://doi.org/10.1038/s41598-025-03232-z

[9] Cho, H., and Korkas, K. K. (2022). High-dimensional GARCH process segmentation with an application to Value-at-Risk. Econometrics and Statistics, 23, 187–203. https://doi.org/10.1016/j.ecosta.2021.07.009

[10] Conrad, C., Inoue, A., and Schienle, M. (2025). Modelling volatility cycles. MF2-GARCH. Journal of Applied Econometrics, 40(2), 592–609. https://doi.org/10.1002/jae.3118

[11] Dinh, D.-H., Do, P., and Hoang, V.-T. (2024). A predictive maintenance policy for manufacturing systems considering degradation of health monitoring device. Reliability Engineering and System Safety, 248(1), 110177. https://doi.org/10.1016/j.ress.2024.110177

[12] Gudkov, N., and Ignatieva, K. (2021). Electricity price modelling with stochastic volatility and jumps. An empirical investigation. Energy Economics, 98, 105260. https://doi.org/10.1016/j.eneco.2021.105260

[13] Huang, Y., and Luo, Y. (2024). Forecasting conditional volatility based on hybrid GARCH-type models with long memory, regime switching, leverage effect and heavy-tail: Further evidence from equity market. *The North American Journal of Economics and Finance, 70*, 102148. https://doi.org/10.1016/j.najef.2024.102148

[14] Ioannidis, F., Papanastasiou, D., and Andriosopoulos, K. (2021). Periodic autoregressive generalized autoregressive conditional heteroscedasticity for electricity spot prices. Energy Economics, 95, 105141. https://doi.org/10.1016/j.eneco.2020.105141

[15] Jalilibal, Z., Amiri, A., Castagliola, P., and Khoo, M. B. C. (2021). Monitoring the coefficient of variation. A literature review. Computers and Industrial Engineering, 161, 107600. https://doi.org/10.1016/j.cie.2021.107600

[16] Javid, Y. (2025). Efficient risk-based inspection framework. Balancing safety and budgetary constraints. Reliability Engineering and System Safety, 253, 110519. https://doi.org/10.1016/j.ress.2024.110519

[17] Kim, C. K., Yoon, M. H., and Lee, S. (2024). Robust control chart for nonlinear conditionally heteroscedastic time series based on Huber support vector regression. PLOS ONE, 19(2), e0299120. https://doi.org/10.1371/journal.pone.0299120

[18] Kripfganz, S., and Schneider, D. C. (2023). ardl: Estimating autoregressive distributed lag and equilibrium correction models. The Stata Journal, 23(4), 983–1019. https://doi.org/10.1177/1536867X231212434

[19] Laurent, S., and Shi, S. (2022). Unit root test with high-frequency data. Econometric Theory, 38(1), 113–171. https://doi.org/10.1017/S0266466621000098

[20] Liu, Y., Li, J., Zhang, Q., and Wang, H. (2022). A new advance prediction method based on SA-LSTMs for energy consumption in cement production. Energy, 241, 122768. https://doi.org/10.1016/j.energy.2021.122768

[21] Liu, Y., Zhou, Z., Huang, H., and Chen, J. (2024). GARCH family models oriented health indicators for bearing degradation monitoring under time-varying conditions. Measurement, 231, 114604. https://doi.org/10.1016/j.measurement.2024.114604

[22] Manis, G., Mishra, A., and Svrcek, W. (2024). Data-driven AI models within a user-defined optimization objective function in cement production. Sensors, 24(4), 1225. https://doi.org/10.3390/s24041225

[23] Meitz, L., Senge, J., and Wagenhals, T. (2025). A literature review framework and open research challenges for predictive maintenance in industry 4.0. Computers and Industrial Engineering, 206(1), 111193. https://doi.org/10.1016/j.cie.2025.111193

[24] Mossie, A. T., Finkbeiner, M., and Madlener, R. (2025). Energy demand flexibility potential in cement industries. How does it contribute to energy supply security and environmental sustainability. Applied Energy, 377, 124608. https://doi.org/10.1016/j.apenergy.2024.124608

[25] Ojeda, J. C. O., and coauthors. (2025). Application of a predictive model to reduce unplanned downtime in industrial systems. Sustainability, 17(9), 3926. https://doi.org/10.3390/su17093926

[26] Pinciroli, G., Baraldi, P., Di Maio, F., and Zio, E. (2023). Maintenance optimization in the era of Industry 4.0. A review. Reliability Engineering and System Safety, 234, 109204. https://doi.org/10.1016/j.ress.2023.109204

[27] Sahoo, N., Kumar, A., and Samsher. (2022). Review on energy conservation and emission reduction approaches for cement industry. Environmental Development, 44, 100767. https://doi.org/10.1016/j.envdev.2022.100767

[28] Yao, Q., and coauthors. (2024). Regularization for high-dimensional multivariate GARCH models. Risks, 12(2), 34. https://doi.org/10.3390/risks12020034

نمذجة التباين الخفي في أداء خط الإنتاج باستخدام بيانات عالية التردد: تطبيق على الشركة العراقية الحكومية لصناعة الإسمنت وتأثيره على استقرار الإنتاج الصناعي

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المستخلص: يقترح البحث الحالي وجود تباين خفي في أداء خطوط الإنتاج كبيانات عالية التردد حول عمليات الشركة العراقية الحكومية لصناعة الإسمنت، ويقيّم تأثير هذا العامل على استقرار الإنتاج الصناعي. تُستخدم الإشارات المُنشأة على إشارات الإنتاج ذات الفترات الزمنية القصيرة لرسم تغيرات أداء الخطوط، ويتم نمذجتها باستخدام نموذج GARCH(1,1) لتقدير تكتل التقلبات واستمراريتها. يتم تقدير التباين الشرطي، وتُسمى النتيجة بالتباين الكامن لأداء الخط (LVP)، ويتم تفسيرها على أنها مؤشر للمخاطر التشغيلية التي تعكس حقيقة وجود عملية إنتاج غير مستقرة. يُعدّ مؤشر استقرار الإنتاج الصناعي (IOS) مؤشرًا للاستقرار المحدود، ويعتمد على تشتت الإنتاج المُحقق عبر الزمن.

ويُضاف إليه كلٌّ من نسبة التوقف غير المخطط له (UDR) واستهلاك الطاقة النوعي (SEC) للحدّ من الصدمات المتعلقة بالموثوقية وكثافة الطاقة. يدعم اختبار جذر الوحدة استنتاج السلاسل الزمنية، مما يثبت استقرار متغيرات الدراسة. تشير نتائج تحليل الانحدار الكمي عند $\tau = 0.30$ إلى أن تقلبات الأداء الكامنة (LVP) لها تأثير سلبي كبير على استقرار النظام (IOS)، مما يوحي بأن زيادة تقلبات الأداء الكامنة تؤدي إلى تدهور الاستقرار حتى عند أخذ عاملي وقت التوقف واستهلاك الطاقة في الاعتبار. يُؤثر معدل الطلب غير المُدار (UDR) تأثيرًا كبيرًا في زعزعة الاستقرار، كما أن استهلاك الطاقة المُتحكم به (SEC) له تأثير سلبي أيضًا، مما يعني أن عدم كفاءة الطاقة يترافق مع أنظمة تشغيل غير مستقرة. تُشير النتائج إلى أن المؤشرات القائمة على التقلبات يُمكن أن تكون أدوات رصد ممتازة للإشارة إلى حالات عدم الاستقرار، كما تُساعد سياسات الصيانة الوقائية وإدارة الطاقة على استقرار إنتاج الصناعات في قطاع صناعة الإسمنت.

الكلمات المفتاحية: نمذجة GARCH - استقرار الإنتاج الصناعي - وقت التوقف غير المخطط له - كثافة الطاقة.

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