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# Building Social Early Warning System (SEWS): Predicting Social Unrest Through Economic Early Warnings

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## ABSTRACT

This study develops a Social Early Warning System (SEWS) to predict unrest by analyzing economic indicators in Jordan. Using the Standardized Index of Social Unrest (SISU), it evaluates key triggers including oil prices, remittances, inflation, income growth, and unemployment. By combining data analytics with historical case validation, the model demonstrates an 83.9% accuracy in forecasting tranquil periods and certain unrest episodes. Although limited in detecting localized events, SEWS offers a practical tool for policymakers to anticipate instability. The study recommends incorporating grassroots data and refining algorithmic thresholds to enhance responsiveness.

**Keywords:** Social Unrest Prediction, Jordan, Signal Detection, Conflict Prevention

## INTRODUCTION

Social unrest—manifested through protests, strikes, and demonstrations—is a collective response to perceived injustice in social, economic, or political systems. It reflects public discontent and often demands reform, ranging from modest policy adjustments to sweeping regime changes. While unrest is context-specific, it consistently signals a breakdown in societal equilibrium.

This study focuses on Jordan, a country that has witnessed five major episodes of social unrest over the past 35 years. Each was shaped by distinct circumstances, yet all shared common roots in economic hardship and perceived governance failures.

The first instance occurred in 1989, when a sharp depreciation of the Jordanian dinar led to soaring prices and subsidy cuts, sparking nationwide protests. A second wave aligned with the Arab Spring (2011–2012), as regional instability reduced foreign investment and trade while amplifying domestic dissatisfaction due to rising inflation, unemployment, and a regressive tax system.

Further unrest erupted in mid-2018 after tax reform proposals increased the burden on citizens. The same year saw continued unrest due to escalating prices and reduced public subsidies. The most recent unrest emerged in 2019 when the teachers' association launched a nationwide strike, underscoring how sector-specific grievances can also disrupt social order.

These episodes underline Jordan's vulnerability to economic shocks and the urgent need for tools that can anticipate unrest before it escalates. This research aims to fill that gap by designing a Social Early Warning System (SEWS) to forecast and mitigate such risks.

### Jordan Case: A Nation on the Edge of Economic and Social Tension

Over the past several decades, Jordan has experienced recurring episodes of social unrest, each underscoring the fragile balance between economic pressure and political stability. The Kingdom's unique geopolitical location—nestled among conflict-prone neighbors—and its dependency on external economic flows have made it particularly vulnerable to both internal and external shocks.

Five notable waves of unrest between 1989 and 2019 have shaped Jordan's contemporary socio-political landscape. The 1989 unrest, triggered by a steep depreciation of the Jordanian dinar and cuts in subsidies, laid bare the population's frustration with deteriorating economic conditions. During the Arab Spring (2011–2012), Jordanians joined a regional chorus of discontent, protesting against unemployment, inflation, and a regressive tax system. Subsequent episodes in 2018 and 2019 were driven by controversial tax reforms and sector-specific grievances, such as the teachers' strike—highlighting that discontent can emerge not only from broad macroeconomic issues but also from perceived injustice within specific professions.

Several persistent and interconnected factors drive Jordan's vulnerability to unrest:

***Economic Hardship and Unemployment***: Jordan's unemployment rate has remained above 20% for years, with youth unemployment among the highest in the world. This has created a disillusioned generation, particularly among university graduates unable to find employment commensurate with their education.

***Strained Infrastructure and Refugee Burden***: Hosting 1.4 million Syrian refugees, along with large numbers of Iraqis, has placed immense pressure on housing, healthcare, education, and employment, especially in low-income communities already struggling with resource scarcity.

***Deterioration of the Social Contract:*** Historically, Jordanians accepted limited political freedoms in exchange for state-provided jobs and subsidies. However, austerity measures, shrinking public sector employment, and subsidy reductions have eroded this implicit social contract, prompting calls for transparency, accountability, and reform.

***Privatization and Inequality:*** Economic reforms and privatization efforts since the 1990s have had mixed outcomes. While aimed at efficiency, they often exacerbated income inequality, weakened the middle class, and fueled public skepticism about the fairness of economic policy.

***Perceptions of Corruption and Ineffective Governance:*** Public confidence in political institutions has been undermined by perceptions of inefficiency, favoritism, and corruption. This sentiment was visible during the 2018 protests, where calls to address structural corruption took precedence over the tax law itself.

***External Dependencies and Economic Fragility:*** Jordan's reliance on foreign aid, remittances, and imports—including energy—makes its economy highly sensitive to regional disruptions and global market volatility. A slowdown in remittance growth, combined with reduced aid from Gulf Cooperation Council (GCC) countries and IMF-imposed austerity measures, has compounded domestic economic woes.

Despite these challenges, the Jordanian Armed Forces continue to command high levels of public trust, often playing a stabilizing role during times of unrest. Their non-aggressive stance during demonstrations in 2011 and 2018 helped maintain a relatively peaceful environment, contrasting with more violent crackdowns seen in other countries.

Nonetheless, public tolerance is wearing thin. The erosion of economic opportunity, rising living costs, and diminished hopes for upward mobility have frayed the threads holding society together. Without meaningful economic reform and inclusive governance, the potential for future unrest remains high.

In light of these conditions, Jordan provides a critical test case for the Social Early Warning System (SEWS). Its complex socio-economic landscape, history of periodic unrest, and current vulnerabilities offer a valuable environment in which to assess the predictive power of SEWS and refine its capacity to anticipate and prevent social disruption.

## REVIEW OF LITERATURE

Social unrest has been studied across disciplines as a multifactorial phenomenon influenced by economic, political, environmental, and social conditions. The literature consistently highlights that unrest does not arise from a single source but from the accumulation of pressures that undermine public trust and stability.

### Economic Hardship and Inequality

Economic stress is one of the most cited drivers of social unrest. High unemployment, inflation, and inequality diminish living standards and fuel public frustration. Little (2014) argues that youth unemployment is a strong predictor of rioting, as it reflects both economic exclusion and lost hope. Justino (2012) supports this by emphasizing how war, conflict, and economic deprivation feed into cycles of poverty and protest. Aisen and Veiga

(2013) add that political instability often stems from poor economic performance, which discourages investment and reduces trust in governance.

Torres (2012) and Nielsen (2013) reject narratives that blame unrest on dependency or entitlement culture. Instead, they stress that growing inequality and limited access to quality employment are more credible triggers. Brancati (2016) likewise finds that institutional inequality, when combined with ineffective governance, increases the likelihood of protest.

### Food Prices and Environmental Stress

Food insecurity emerges as another important catalyst, particularly in the Middle East and North Africa (MENA) region. Johnstone and Mazo (2011) argue that rising global food prices in 2010–2011, compounded by droughts and export restrictions, played a major role in igniting the Arab Spring. Lagi, Bertrand, and Bar-Yam (2011) take this further, proposing a global food price index threshold (FPI > 210) beyond which unrest becomes likely.

Environmental degradation also features in this discourse. Whittle (2017) shows how climate shocks—like droughts—can lead to mass migration and displace economic stability, which in turn increases societal tensions. The Food and Agriculture Organization of the United Nations (**FAO)** and UNDP have echoed these concerns, emphasizing how fragile ecosystems can become flashpoints when basic needs are unmet.

### Social Identity and Grievance Mobilization

From a sociological perspective, group identity and perceived injustice are fundamental. Gurr (1970) introduces the theory of relative deprivation, suggesting that when expectations rise faster than actual improvements in living conditions, societies become ripe for unrest. Polsby and Haddock (1994, 2016) analyze crowd dynamics, noting how spontaneous collective action—often incited by symbolic acts—can quickly escalate into full-scale unrest. Buford (1991) further highlights how anonymity in large groups lowers inhibitions and increases the likelihood of violence.

These ideas converge on the concept of perceived fairness. When individuals believe they are treated unjustly—whether due to discrimination, corruption, or income gaps—they are more likely to join protests, especially when they identify strongly with a marginalized group.

### Digital Platforms and Mobilization Cascades

Digital communication is an increasingly important variable in understanding social unrest. Cadena et al. (2015) show how social media "cascades" can rapidly disseminate dissent and coordinate mobilization. Their work demonstrates that tweets and online networks often serve as early indicators of upcoming unrest.

However, Barakat (2013) provides a more cautious view in the Jordanian context. She argues that digital tools alone are insufficient to transform institutions unless governments support structural reforms. This reflects a broader theme: while technology can amplify voices, it does not guarantee systemic change.

### Institutional Trust and Governance Legitimacy

Institutional legitimacy is a recurring theme in the literature. Beissinger (2002) shows how nationalist movements challenge weak or illegitimate regimes, often using social unrest to provoke systemic change. Sen (1999) links democratic governance to sustained economic growth and political stability, arguing that transparent institutions reduce the risk of unrest.

Stark, Hyll, and Behrens (2010) contribute two key predictive tools: the polarization index (which gauges conflict between identity groups) and the relative deprivation index (which assesses economic grievance). Their findings suggest that unrest is more likely in environments where trust in government erodes and socioeconomic divisions widen.

### Multifactorial and Context-Specific Models

Efforts to model unrest underscore its complexity. Barton et al. (2008) reviewed 30 conflict prediction models and identified over 800 unique indicators, ranging from inflation and poverty rates to regime legitimacy and access to public services. They stress the need for both long-term structural indicators and short-term economic variables in effective early warning systems.

Similarly, the UNDP and OAS (2016) emphasize integrating early warning with response mechanisms that are sensitive to both the causes and escalation pathways of unrest. Their guide encourages governments to not only monitor risk but also build institutional capacity to intervene ethically and effectively.

 

## METHODOLOGY

This study employs a predictive modeling approach to develop the Social Early Warning System (SEWS), using quarterly economic data from Jordan. The core of the methodology is the construction and validation of the Standardized Index of Social Unrest (SISU), which serves as a composite indicator designed to detect early warning signs of social instability.

### Data Framework and Temporal Resolution

A quarterly time series dataset was used to capture fluctuations in economic and social conditions over time. The model was retrospectively tested against major episodes of unrest in Jordan, including the 2011–2012 Arab Spring and the 2018 protests sparked by tax reforms. These historical validations were essential to assess SISU's predictive accuracy.

### Variable Selection

Key variables were identified based on the literature review and their demonstrated significance in prior unrest studies. The model incorporates five core indicators:

- Growth in oil prices
- Net remittance rates
- Inflation rate
- Growth of per capita income
- Unemployment rate

These variables were selected for their macroeconomic relevance and their statistical sensitivity to periods of unrest in the Jordanian context.

### Model Design and Purpose

The SISU index was formulated to synthesize the above indicators into a single predictive score. When this score exceeds a defined threshold—set at 1.4 standard deviations above the historical mean—it triggers a warning signal for potential unrest.

The goal is not to forecast specific events with perfect precision, but to provide policymakers with an evidence-based, timely alert system. This enables intervention before grievances escalate into broader societal disruption.

### Analytical Approach

The methodological approach combines descriptive statistics, time-series analysis, and signal classification using a contingency matrix. This allows for the evaluation of false positives and false negatives, and the overall signal-to-noise ratio of the model. This combination enhances reliability while allowing for iterative refinement of the model's parameters.

### Social Unrest Model

To understand and anticipate social unrest in Jordan, this model evaluates five core economic indicators shown to correlate with societal instability. These variables—when combined—form the foundation of the Standardized Index of Social Unrest (SISU), which aims to signal heightened risk of unrest when certain thresholds are surpassed.

### Key Predictive Variables

***Oil Price Growth:*** As Jordan imports nearly all of its energy, fluctuations in global oil prices significantly affect domestic living costs and inflation. A sharp rise in oil prices can quickly erode household purchasing power and trigger discontent.

***Net Remittance Rates:*** Remittances represent a vital income stream for many Jordanian households. The model considers both inflows from Jordanians abroad and outflows by expatriates in Jordan. A decline in net remittances can reduce financial resilience, especially for lower-income families.

***Inflation Rate:*** With Jordan's per capita income hovering around $4,000, inflation directly impacts affordability. Rising prices for essential goods amplify hardship and can spark public frustration.

***Per Capita Income Growth:*** A stagnation or decline in income levels contributes to perceptions of economic exclusion. When citizens feel their financial prospects are worsening, unrest becomes more likely.

***Unemployment Rate Growth:*** Although Jordan's unemployment rate has remained high, it is the *rate of increase*—especially among youth—that more strongly correlates with unrest. Rapid jumps in joblessness often precede protest activity.

### The SISU Formula

To integrate these variables, the model applies the following expression:

SISU = (Growth rate of oil prices) – (Growth rate of net remittances) + Inflation rate – (Growth rate of GDP per capita) + (Growth rate of unemployment)

This formulation allows SISU to quantify unrest risk in a single, interpretable index.

### Evaluation Criteria

To assess the model's effectiveness, several criteria are used:

***Minimizing Type I Errors (Missed Predictions):*** Essential to avoid being caught off guard by unrest.
***Minimizing Type II Errors (False Alarms):*** Helps prevent unnecessary policy overreactions.
***Signal-to-Noise Ratio:*** Ensures that generated alerts are meaningful and timely.
***Overall Predictive Accuracy:*** Evaluates how consistently the model anticipates both unrest and stable periods.

This model provides a practical tool for forecasting unrest in Jordan by capturing the economic undercurrents that often precede mass mobilization. The next section will explore how this model is formalized and tested within the broader SEWS framework.

#### Standardized Model of Early Warning System

The Social Early Warning System (SEWS) centers on the development and validation of the Standardized Index of Social Unrest (SISU)**,** a composite metric designed to anticipate periods of societal instability. SISU operates by aggregating economic indicators that have historically shown predictive power during previous episodes of unrest in Jordan.

#### Threshold Calibration and Signal Triggering

The SISU model issues an alert when its score exceeds 1.4 standard deviations above the mean of its historical distribution. This threshold was determined through back-testing against known instances of unrest—such as the Arab Spring (2011–2012) and the nationwide protests in mid-2018. A SISU score below the threshold suggests low risk; a score above indicates a heightened probability of disruption.

#### Matrix of Signals and Crisis

The following matrix represents the model's predictions and actual outcomes:

| | **Social unrest Occurred** | **No Social unrest Occurred** | **Total** |
|---|---|---|---|
| **Prediction of the model** | 3 (A) | 8 (B) | 11 |
| **No Prediction of the model** | 6 (C) | 70 (D) | 76 |
| **Total** | 9 | 78 | 87 |

**A**: Quarters where the model correctly predicted unrest.
**B**: False positives (signals during tranquil periods).
**C**: Missed predictions (unrest occurred but no signal).
**D**: Quarters correctly identified as tranquil.

#### Performance Metrics and Predictive Accuracy

To assess the SISU's reliability, the model uses a contingency matrix comparing predicted versus actual periods of unrest. Performance is measured across four dimensions:

**Type I Error** (missed unrest): 66.7%
**Type II Error** (false alarms): 10.25%
**Correct Predictions** (either unrest or stability): 83.91%
**Correct Tranquility Predictions**: 89.74%

These results indicate that while the model is highly effective at recognizing periods of calm, it is somewhat limited in capturing unrest events that are localized or issue-specific—such as sectoral strikes or short-term protests.

#### Implications for Policy and Governance

Despite its limitations, SISU serves as a critical decision-support tool. Its greatest strength lies in its ability to signal systemic risk before protests escalate. This enables governments, international donors, and civil society actors to respond proactively rather than reactively.

 

The model's utility can be enhanced through:

- Integration of real-time data (e.g., social media sentiment)
- Inclusion of geographic and sectoral disaggregation
- Regular model recalibration based on emerging trends

In sum, the SISU is a foundational pillar of SEWS—a scalable framework capable of identifying early signals of unrest and informing timely, evidence-based responses.

## FINDINGS

### Model Performance

The SISU model showed encouraging potential in detecting periods of social unrest. It successfully predicted three out of nine major episodes, including the onset and conclusion of the Arab Spring in Jordan, which spanned from January 14, 2011, to November 18, 2012. However, it did not capture the six quarters of unrest that occurred between those two points. Where the model truly excelled was in identifying stable periods—accurately recognizing nearly 90% of the tranquil quarters, highlighting its reliability in signaling social calm.

This suggests that SISU is a valuable tool for validating stability and offers confidence in its predictive reliability under normal conditions.

## LIMITATIONS

However, the model struggled to detect localized or sector-specific unrest. For instance, it failed to anticipate the 2019 teachers' strike—an event with limited macroeconomic footprint but significant social repercussions. The primary reason lies in SISU's dependence on broad, national-level economic indicators, which may not capture nuances such as labor disputes or politically symbolic protests.

This limitation highlights the need to supplement SISU with granular, real-time inputs, such as social media trends, regional data, or signals from specific public sectors.

## POLICY IMPLICATIONS

Despite its imperfections, SISU offers an important early warning mechanism for governments, development agencies, and financial institutions. By identifying periods of heightened risk, the model allows for:

- Preemptive policy adjustments
- Targeted communication strategies
- Increased monitoring of at-risk communities

In contexts like Jordan—where economic fragility and public dissatisfaction can escalate quickly—SISU can inform preventative governance rather than reactive crisis management.

## CONCLUSION

The Standardized Index of Social Unrest (SISU) offers a valuable framework for understanding the economic precursors of social unrest in Jordan. While the model excels in identifying stable periods with high accuracy, its moderate success in predicting unrest events highlights important areas for refinement—particularly the need for localized, sector-specific data.

This study confirms that certain economic indicators—such as oil prices, remittance flows, inflation, per capita income growth, and unemployment—are consistently linked to unrest dynamics. These variables not only influence household welfare, but also reflect broader social frustrations, especially among youth and vulnerable populations.

Jordan's economic vulnerability—due to high dependence on imported energy, foreign aid, and remittances—makes it particularly sensitive to global shocks. In such a context, the early detection capabilities of SISU can help mitigate risks before discontent turns into instability.

However, the model's full potential lies in being part of a holistic strategy. Predictive analytics must be coupled with long-term structural reforms aimed at poverty reduction, job creation, education, and inclusive governance. SISU can guide policy timing, but it cannot replace the need for addressing the root causes of social unrest.

Ultimately, SEWS represents a proactive shift in managing societal risks. By enabling timely interventions and data-informed decisions, it provides a foundation for more resilient, equitable, and responsive governance.

 

## RECOMMENDATIONS

To maximize the utility and impact of the Social Early Warning System (SEWS), this study proposes the following strategic enhancements:

### *Ethical Oversight and Interdisciplinary Design*

Beyond technical and economic expertise, SEWS should involve ethicists and data privacy experts. This ensures that data collection and analysis respect individual rights and avoid misuse, particularly in politically sensitive contexts.

### *Culturally Sensitive AI-Driven Social Media Analysis*

Integrating artificial intelligence for real-time monitoring of social media can strengthen predictive accuracy. However, these tools must be attuned to cultural nuances, local dialects, and misinformation trends. Transparency in data interpretation is essential to building public trust.

### *Machine Learning for Adaptive Updating*

SEWS should evolve dynamically through machine learning. As unrest drivers shift, the model must adapt to new patterns without requiring constant manual recalibration. This ensures its continued relevance and accuracy.

### *Stakeholder Roles and Centralized Coordination*

For SEWS to function efficiently, clear roles and accountability mechanisms must be established among stakeholders. A central governing body—possibly housed within a ministry or independent agency—should oversee implementation, data governance, and inter-agency coordination.

### *Policy Scenario Planning*

Governments should not wait for alerts to act. Scenario planning and stress testing should be integrated into policy development, allowing for proactive strategies that mitigate unrest before it materializes.

### *Public Engagement and Communication*

Effective communication is key to managing public expectations. SEWS outputs should be translated into accessible, anonymized insights and shared through public awareness campaigns. Transparency can prevent misinformation and enhance citizen cooperation.

### *Incorporating Grassroots Data*

In addition to institutional and digital data, SEWS should tap into grassroots sources such as local NGOs, community reports, and citizen feedback. These bottom-up insights can fill critical gaps and improve the system's responsiveness to localized tensions.

### *Long-Term Structural Reform Integration*

Finally, SEWS must be part of a broader commitment to reform. Addressing inequality, improving education and healthcare, and expanding economic opportunity are essential for long-term social stability. SEWS can guide *when* to act, but real impact comes from *what* is done.

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| | **Growth Rate of Oil Price** | **Growth Rate of Net Remittances** | **Inflation Rate** | **Growth Rate of GDP per Capita** | **Growth Rate of Unemployment Rate** | **Index of Social Unrest (ISU) = Growth Rate Price of Oil Minus Growth Rate of Net Remittances plus Inflation Rate Minus Growth Rate of GDP Per Capita Plus Growth Rate of Unemployment** | **Standardized Index of Social Unrest (SISU)** |
|---|---|---|---|---|---|---|---|
| 1999 Q4 | | | | | | | |
| 2000 Q1 | 0.054132 | -0.04333 | 0.099505 | -8.87424 | 0.367034 | | |
| 2000 Q2 | 0.049392 | 0.211408 | -0.09941 | 9.911605 | -0.07876 | | |
| 2000 Q3 | 0.145685 | 0.104634 | -0.34604 | 3.688638 | 0.00944 | 9.438243 | 1.27435 |
| 2000 Q4 | -0.03097 | -0.08796 | -0.79434 | -0.05724 | 0.023492 | -10.2518 | -1.20675 |
| 2001 Q1 | -0.12954 | -0.04636 | 1.451169 | -9.48405 | 0.148757 | -3.98419 | -0.41698 |
| 2001 Q2 | 0.054117 | 0.154415 | 0.592303 | 9.792228 | -0.1573 | -0.65662 | 0.002316 |
| 2001 Q3 | -0.07224 | 0.016509 | 1.276257 | 5.181478 | 0.126482 | 11.0008 | 1.471245 |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| 2001 Q4 | -0.23518 | 0.017236 | 0.193314 | -1.09431 | 0.000201 | -9.45752 | -1.10667 |
| 2002 Q1 | 0.09199 | -0.12317 | 0.919734 | -9.42301 | -0.00878 | -3.86749 | -0.40228 |
| 2002 Q2 | 0.185518 | 0.154218 | 0.191183 | 9.937549 | 0.039757 | 1.035415 | 0.215526 |
| 2002 Q3 | 0.07505 | 0.093046 | -0.28694 | 6.221163 | 0.074132 | 10.54912 | 1.414329 |
| 2002 Q4 | -0.00706 | -0.05214 | -0.0964 | -0.66499 | -0.1341 | -9.67531 | -1.13411 |
| 2003 Q1 | 0.178758 | -0.10597 | 1.489205 | -11.4563 | 0.084458 | -6.45197 | -0.72794 |
| 2003 Q2 | -0.16973 | 0.120612 | 0.851462 | 11.40907 | -0.11959 | 0.479575 | 0.145486 |
| 2003 Q3 | 0.087123 | 0.045285 | 0.374295 | 6.684677 | 0.098492 | 13.31466 | 1.76281 |
| 2003 Q4 | 0.03304 | -0.0638 | 0.748602 | -1.52786 | -0.07513 | -10.9675 | -1.29694 |
| 2004 Q1 | 0.086084 | -0.05357 | 0.32421 | -6.25536 | -0.03517 | -6.17005 | -0.69242 |
| 2004 Q2 | 0.110589 | 0.067649 | 1.987517 | 12.63825 | -0.06865 | 2.298172 | 0.374644 |
| 2004 Q3 | 0.16756 | 0.061794 | -0.67997 | 4.426846 | 0.132911 | 6.684044 | 0.927299 |
| 2004 Q4 | 0.066924 | -0.01448 | 0.684622 | -1.92511 | -0.02967 | -10.6764 | -1.26026 |
| 2005 Q1 | 0.080163 | -0.03837 | 1.587043 | -8.27483 | -0.02131 | -4.86814 | -0.52837 |
| 2005 Q2 | 0.08239 | 0.0399 | -0.53548 | 14.85032 | 0.174607 | 2.66147 | 0.420422 |
| 2005 Q3 | 0.190587 | 0.014988 | 2.69179 | 3.352247 | 0.054268 | 9.959101 | 1.339982 |
| 2005 Q4 | -0.07467 | -0.01536 | 1.878113 | 1.567698 | -0.19856 | -15.1687 | -1.82632 |
| 2006 Q1 | 0.085619 | -0.0072 | -19.2436 | -3.11596 | 0.079703 | -0.43059 | 0.030798 |
| 2006 Q2 | 0.125992 | 0.16284 | 2.74142 | 13.42756 | -0.0885 | 0.052546 | 0.091677 |
| 2006 Q3 | 0.001294 | 0.124968 | 0.704487 | 6.807407 | 0.176093 | -15.9552 | -1.92542 |
| 2006 Q4 | -0.14278 | -0.11617 | 1.718388 | -1.01972 | -0.15687 | -10.8115 | -1.27728 |
| 2007 Q1 | -0.03217 | 0.076561 | 1.599781 | -5.51791 | 0.102763 | -6.0505 | -0.67736 |
| 2007 Q2 | 0.187327 | 0.079126 | -0.18422 | 9.385183 | -0.24843 | 2.554629 | 0.406959 |
| 2007 Q3 | 0.092884 | 0.123032 | 0.392739 | 8.077131 | 0.324789 | 7.11172 | 0.98119 |
| 2007 Q4 | 0.18559 | -0.06469 | 2.812833 | 0.04684 | -0.09072 | -9.70963 | -1.13844 |
| 2008 Q1 | 0.09093 | -0.06702 | 6.545091 | 3.776121 | 0.086662 | -7.38975 | -0.84611 |
| 2008 Q2 | 0.252321 | 0.190498 | 4.268945 | 12.60643 | -0.11132 | 2.925557 | 0.453699 |
| 2008 Q3 | -0.05766 | 0.066127 | 3.489906 | 13.68027 | -0.03864 | 3.013585 | 0.464792 |
| 2008 Q4 | -0.5222 | -0.20561 | -1.4895 | -9.21195 | -0.00706 | -8.38698 | -0.97177 |
| 2009 Q1 | -0.18716 | -0.02003 | -3.3081 | -0.14847 | 0.012044 | -10.3528 | -1.21948 |
| 2009 Q2 | 0.321179 | 0.172125 | -0.31335 | 1.363626 | 0.07438 | 7.398793 | 1.017363 |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| 2009 Q3 | 0.16184 | 0.00436 | 2.069296 | 1.357531 | 0.076923 | -3.3147 | -0.33262 |
| 2009 Q4 | 0.094282 | -0.09688 | 0.931438 | 12.66629 | -0.12857 | -1.45354 | -0.0981 |
| 2010 Q1 | 0.021707 | -0.03539 | 1.900236 | -8.795 | 0.016393 | 0.946168 | 0.20428 |
| 2010 Q2 | 0.029639 | 0.075198 | 0.201566 | 1.384089 | -0.01613 | -11.6723 | -1.38574 |
| 2010 Q3 | -0.02153 | 0.118812 | 1.021674 | 1.384089 | 0.106557 | 10.76873 | 1.442002 |
| 2010 Q4 | 0.125618 | -0.07701 | 2.214146 | 16.4572 | -0.12593 | -1.24421 | -0.07173 |
| 2011 Q1 | 0.213831 | -0.06263 | 0.559418 | -12.2838 | 0.110169 | -0.3962 | 0.035132 |
| 2011 Q2 | 0.11814 | 0.010881 | 0.892229 | 0.757216 | 0.007634 | -14.1664 | -1.70002 |
| 2011 Q3 | -0.03425 | 0.064801 | 0.873475 | 0.757216 | -0.00758 | 13.22989 | 1.752128 |
| 2011 Q4 | -0.03476 | -0.07339 | 0.893887 | 13.41654 | -0.07634 | 0.249906 | 0.116546 |
| 2012 Q1 | 0.08309 | -0.03971 | 0.616836 | -11.1156 | -0.05785 | 0.009629 | 0.086269 |
| 2012 Q2 | -0.08499 | 0.160873 | 1.637344 | 0.052058 | 0.017544 | -12.5604 | -1.49765 |
| 2012 Q3 | 0.010976 | 0.077706 | 1.666616 | 0.052058 | 0.12931 | 11.79734 | 1.571615 |
| 2012 Q4 | 0.004379 | -0.20069 | 1.695216 | 10.04866 | -0.03053 | 1.356971 | 0.256045 |
| 2013 Q1 | 0.0218 | 0.047716 | 1.320059 | -8.97312 | 0.007874 | 1.677138 | 0.296388 |
| 2013 Q2 | -0.0881 | 0.174799 | 0.060935 | 0.121734 | -0.01563 | -8.17891 | -0.94555 |
| 2013 Q3 | 0.074966 | 0.022522 | 1.302156 | 0.121734 | 0.111111 | 10.27514 | 1.379806 |
| 2013 Q4 | -0.00961 | -0.12421 | 0.913124 | 12.41616 | -0.21429 | -0.33932 | 0.042298 |
| 2014 Q1 | -0.00952 | -0.01752 | 0.964173 | -11.5274 | 0.072727 | 1.343977 | 0.254407 |
| 2014 Q2 | 0.014329 | 0.152749 | 0.219595 | -0.66345 | 0.016949 | -11.6027 | -1.37698 |
| 2014 Q3 | -0.072 | -0.00182 | 0.78198 | -0.66345 | -0.05 | 12.57231 | 1.669269 |
| 2014 Q4 | -0.24966 | -0.08625 | 0.017211 | 9.505654 | 0.078947 | 0.761572 | 0.18102 |
| 2015 Q1 | -0.29424 | -0.02415 | -1.9218 | -10.8283 | 0.04878 | 1.325246 | 0.252047 |
| 2015 Q2 | 0.144102 | 0.135787 | 0.831371 | -1.69983 | -0.14729 | -9.5729 | -1.12121 |
| 2015 Q3 | -0.18577 | 0.025567 | 0.245381 | -1.69983 | 0.254545 | 8.685235 | 1.179465 |
| 2015 Q4 | -0.13259 | -0.10709 | -0.56116 | 5.617186 | -0.01449 | 2.39223 | 0.386496 |
| 2016 Q1 | -0.22653 | -0.09792 | -1.66027 | -8.29412 | 0.073529 | 1.988422 | 0.335613 |
| 2016 Q2 | 0.350742 | 0.185048 | 0.326975 | 0.839133 | 0.006849 | -6.21833 | -0.6985 |
| 2016 Q3 | 0.005931 | 0.000184 | 1.344513 | -0.02245 | 0.07483 | 6.578759 | 0.914032 |
| 2016 Q4 | 0.074252 | -0.04781 | 0.280334 | 5.889053 | 0 | -0.33962 | 0.042261 |
| 2017 Q1 | 0.091279 | -0.10912 | 1.787674 | -10.6206 | 0.151899 | 1.447536 | 0.267457 |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| 2017 Q2 | -0.0747 | 0.145892 | 0.181905 | 4.133071 | -0.01099 | -5.48666 | -0.60631 |
| 2017 Q3 | 0.049124 | 0.000946 | 0.27445 | 12.43574 | 0.027778 | 12.76052 | 1.692984 |
| 2017 Q4 | 0.180771 | -0.05273 | 1.073744 | -1.80617 | 0 | -4.18275 | -0.442 |
| 2018 Q1 | 0.085812 | -0.10196 | 2.292134 | -11.9073 | -0.00541 | -12.0853 | -1.43779 |
| 2018 Q2 | 0.115103 | 0.128194 | 0.992464 | 4.003775 | 0.016304 | 3.113412 | 0.47737 |
| 2018 Q3 | 0.009664 | 0.008074 | 0.710371 | 11.19699 | -0.00535 | 14.38175 | 1.897272 |
| 2018 Q4 | -0.09984 | -0.02833 | 0.081904 | -1.41232 | 0.005376 | -3.0081 | -0.29399 |
| 2019 Q1 | -0.06705 | -0.01407 | -0.8562 | -11.1082 | 0.016043 | -10.4904 | -1.23682 |
| 2019 Q2 | 0.091024 | 0.054649 | 0.901804 | 3.481609 | 0.010526 | 1.428082 | 0.265005 |
| 2019 Q3 | -0.10142 | 0.002707 | 0.397219 | 12.18354 | -0.00521 | 10.21502 | 1.37223 |
| 2019 Q4 | 0.023898 | -0.03317 | 0.296736 | 0.320916 | -0.00524 | -2.5329 | -0.23411 |
| 2020 Q1 | -0.20454 | -0.06921 | 0.30572 | -12.3867 | 0.015789 | -11.8957 | -1.41389 |
| 2020 Q2 | -0.41832 | -0.02378 | -1.09134 | -3.11387 | 0.186528 | 0.027649 | 0.088539 |
| 2020 Q3 | 0.464213 | 0.063872 | 0.198807 | 12.4882 | 0.043668 | 12.57287 | 1.669339 |
| 2020 Q4 | 0.030959 | 0.02909 | 0.496032 | 0.32559 | 0.033473 | 1.814525 | 0.3137 |
| 2021 Q1 | 0.373222 | -0.04711 | 0.47384 | -10.278 | 0.012146 | -11.8454 | -1.40756 |
| 2021 Q2 | 0.1317 | -0.08332 | 0.412655 | 0.962386 | -0.008 | 0.205784 | 0.110986 |
| 2021 Q3 | 0.026006 | 0.063117 | 0.684932 | 0.671377 | -0.06452 | 11.18432 | 1.49437 |
| 2021 Q4 | #VALUE! | 0.000648 | 0.291545 | 11.00095 | 0.00431 | -0.34272 | 0.041871 |
| 2022 Q1 | #VALUE! | -0.01942 | 0.484496 | 0.932612 | -0.02146 | -0.08807 | 0.073958 |
| 2022 Q2 | 0.151085 | -0.00572 | 2.217936 | -9.99085 | -0.00877 | | |
| 2022 Q3 | -0.1434 | 0.033857 | 1.792453 | 2.343163 | 0.022124 | | |
| 2022 Q4 | -0.11103 | -0.29946 | 0.370714 | 12.0018 | -0.00866 | | |
| 2023 Q1 | | | | | 0 | | |
| | | | | | Average | -0.67486 | 1.81E-05 |
| | | | | | Std dev | 7.936413 | 1.000052 |