AGORA International Journal of Economical Sciences, http://univagora.ro/jour/index.php/aijes
ISSN 2067-3310, E-ISSN 2067-7669
Vol. 18, No. 2 (2024), pp. 300-319

THE EXPERIENCE OF ILLNESS: EMOTIONAL AND ECONOMIC IMPACTS

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Abstract: *This study examines the complex emotional and economic consequences of illness, focusing on individuals' subjective experiences and their broader societal impact. Employing a multi-level methodological approach, it combines theoretical insights with wavelet transform analysis to investigate long-term sickness trends in the UK. The findings highlight a significant increase in economically inactive individuals due to long-term sickness, driven by factors such as mental health conditions, chronic diseases, and the COVID-19 pandemic. The emotional aspects of illness are explored through their influence on relationships, personal identity, and societal attitudes, underscoring the necessity of patient-centered care that addresses both psychological and social needs. The economic analysis reveals the substantial burden of illness manifested in decreased labor force participation, rising healthcare costs, and productivity losses. Wavelet transform analysis captures both short-term variations and long-term patterns, offering valuable insights into the dynamic, non-stationary nature of sickness-related economic inactivity. This research emphasizes the critical need for proactive healthcare policies, workplace accommodations, and robust mental health support to reduce the adverse effects of illness on individuals and economies. By integrating advanced analytical methods and interdisciplinary perspectives, the study enhances our understanding of the intricate connections between illness, emotional health, and economic resilience.*
Keywords: *economic impact of illness; emotional impact; experience of illness.*

INTRODUCTION

The world is facing a persistent global mental health crisis exacerbated by the COVID-19 pandemic, rising living costs, and increasing global challenges. These factors have intensified pre-existing issues and created more significant uncertainty for many. According to the World Health Organization, approximately 15% of the global working-age population experiences mental illness, impacting not only individual well-being and relationships but also the workplace. Depression and anxiety are estimated to cost the global economy $1 trillion annually, equating to 12 billion lost workdays. A recent Deloitte study highlights the significant mental health challenges faced by Gen Z and millennials, who comprise a large portion of the workforce. The research found that 40% of Gen Zs and 35% of millennials report feeling stressed or anxious most of the time, with nearly half experiencing workplace burnout.

The experience of illness is a highly relevant topic with profound implications for healthcare, policy, and society. Exploring this subject can deepen our understanding of how illness affects individuals physically, emotionally, and socially beyond what traditional biomedical models capture. It can also highlight the diversity of personal responses to illness and the role of cultural, psychological, and social factors in shaping those experiences.

From a scientific perspective, studying the experience of illness can lead to improved patient-centered care, as it helps healthcare professionals recognize and respond to patients' unique needs and perspectives. It can inform interventions that address not only the symptoms but also the psychosocial aspects of illness, improving overall quality of life for patients.

The experience of illness is a multifaceted phenomenon encompassing many personal, social, and cultural dimensions. It is not merely about the physical symptoms but also involves the individual's subjective experience, which includes changes in self-identity, time perception, and existential meaning, as highlighted by Havi Carel's phenomenological analysis (Carel, 2015). The diagnosis process plays a crucial role in shaping the illness experience, as it involves navigating complex power dynamics and social interactions that can significantly impact how patients perceive and manage their conditions (Jeske et al., 2023). Moreover, the experience of illness is deeply intertwined with the search for meaning as individuals and caregivers grapple with questions about the purpose of life amidst suffering. This search for meaning can lead to either despair or a heightened sense of awareness and responsibility, serving as a therapeutic resource (Bruzzone, 2021). The social construction of illness further complicates this experience, as it is influenced by cultural norms and societal values, which shape how individuals interpret and respond to their conditions (Skrzypek, 2014). Illness narratives, which are personal stories about living with illness, provide valuable insights into these experiences, though they must be critically examined for their epistemological properties to ensure they accurately reflect the realities of the individuals' experiences (Lucius-Hoene et al., 2018). Additionally, the patient experience is a complex construct that includes determinants such as the quality of healthcare services and the politics of healthcare, which influence patient satisfaction and engagement (Zakkar, 2019). Overall, understanding the experience of illness requires a holistic approach that considers the interplay of personal, social, and systemic factors, as well as the narratives and meanings individuals ascribe to their experiences (Locock et al. (2017), Cipolletta, (2020), Palmeira & Gewehr (2018)).

The experience of illness is a profoundly personal and often life-altering journey, shaped by a range of physical, emotional, and psychological challenges. Unlike clinical definitions that focus on biological abnormalities and diagnostic criteria, the experience of illness is subjective, encompassing how individuals perceive, interpret, and react to their health conditions. This viewpoint enlightens the lived reality of patients, revealing how illness interrupts daily routines, reshapes identities, and affects relationships (Shrout et al., 2024). Studying the experience of illness uncovers symptoms and treatments and the intricate connections between the body, mind, and society. While healthcare professionals focus on diagnosis and treatment, the experience of illness highlights how individuals interpret their suffering and adapt to the changes it brings. This process involves many emotions—from fear and uncertainty to resilience and acceptance—and emphasizes the significant influence of culture, family, and personal beliefs on how illness is understood. Acknowledging the experience of illness is crucial for healthcare providers, as it bridges the divide between clinical care and patient-centered support, promoting empathy and comprehensive approaches that consider both medical and personal dimensions.

This paper aims to identify theoretical aspects of the emotional and economic impacts of illness and create a methodology to value the effect of COVID-19 on illness and stress.

This paper is organized as follows: Section 2 gives insights into the theoretical basis of understanding illness's emotional and economic impact. Section 3 analysing the research methodology focusing on the idea of wavelet transformation. Section 4 describes the results and discussion, and finally, we present our conclusions and recommendations.

LITERATURE REVIEW

Emotional impact

Illness significantly impacts relationships, often transforming them in complex ways. Long-term illness can lead to positive and negative social network changes, as individuals may experience increased support from family and friends. At the same time, some relationships may become distant or dissolve due to the strain of illness. Long-term illnesses can lead to shifts in social networks, with some relationships becoming more supportive while others diminish, reflecting the complex nature of social support during illness (Espvall & Dellgran, 2016). Chronic illness, mainly when concealable, can challenge couples' communication and relational well-being, often resulting in lower satisfaction and increased burden. However, when couples engage in open communication and dyadic coping strategies, they can enhance their relational satisfaction and closeness (Shrout et al., 2023). Emotionally focused therapy has been shown to help couples enrich their emotional quality, allowing them to express deep-seated emotions and meet each other's needs despite the challenges posed by chronic illness (Chawla & Kafescioglu, 2012). The stress of illness can also lead to role changes within relationships, where partners may need to take on additional responsibilities, potentially leading to feelings of resentment and grief on both sides (Campling & Sharpe, 2008). Communication-debilitating illnesses further complicate relationships by necessitating adjustments in how individuals interact with loved ones, often requiring new strategies to maintain relational bonds (Bute et al., 2007). In young adults, chronic illness can disrupt normative relationship development, leading to insecure attachments and lower relationship satisfaction compared to healthy peers (Cole & Karantzas, 2006). Family dynamics are also affected, as serious illness can lead to protective behaviors that isolate family members from one another when mutual support is most needed. Chronic illness in children also affects family dynamics, with older children experiencing weaker family relationships, although these relationships can be strengthened by better health and reduced anxiety or depressive symptoms (Cox et al., 2021). Despite these challenges, sharing personal narratives and life challenges can help individuals with chronic illnesses redefine their identities and foster healthier relationships with family and friends (Huang et al., 2018). Chronic illness profoundly transforms relationships, highlighting the resilience and adaptability of individuals and their social networks as they navigate evolving challenges and roles.

Individuals experiencing illness frequently exhibit diverse emotional responses characterized by complexity and nuance. Common emotional responses include feelings of depression, anxiety, fatigue, and a desire to limit social interactions, collectively known as the sickness response, which is an adaptive behavior aimed at conserving energy and improving survival during illness (Lekander, 2022). This response is functionally similar to classical emotions like fear and can be exacerbated by low-grade inflammation, contributing to symptoms in both somatic and mental health contexts (Lekander, 2022). Emotional reactions to illness are not only individual but also relational, affecting family dynamics and manifesting in themes such as denial versus acceptance, despair versus hope, and isolation versus connection (McDaniel et al., 2000). The phenomenological perspective, as discussed by Madeira et al. (2019), introduces the concept of the "uncanny" in illness, where individuals experience a disconcerting shift in their sense of being, leading to feelings of fear and loss of control (Madeira et al., 2019). The severity of the illness does not always correlate with the intensity of psychological reactions, as even minor illnesses require lifestyle adjustments and can lead to significant emotional distress, including anxiety and depression (G. G. Lloyd, 2007). A lack of empathy from others can further exacerbate the emotional burden of illness, leading to feelings of isolation and frustration (Havi, 2008). The author reflects on the emotional toll of experiencing rapid physical decline at a young age, noting the anxiety and dread that accompany each deterioration in health. This includes concerns about losing the ability to engage in once-manageable activities, leading to a shrinking world and a sense of helplessness (Havi, 2008). While fear and sadness are common, they are often normal emotional responses to the threat posed by illness, and understanding these emotions can aid in better patient adaptation and management (Bowman, 2001). The paper concludes that the traditional psychopathological paradigm, which primarily emphasizes anxiety and depression as indicators of patient reactions to acute illness, is insufficient due to the considerable variability in how these emotions are measured and interpreted across different populations. It calls for a shift in perspective, advocating for recognizing emotional responses to illness as normal reactions rather than pathological ones, and suggests that future research should adopt this approach to enhance the understanding of patient experiences. (Bowman, 2001) Individuals facing illness often experience a complex spectrum of emotions, including fear, sadness, anger, guilt, and isolation, alongside moments of hope, gratitude, and acceptance. These emotions, shaped by personal and social contexts, evolve and reflect the profound psychological impact of living with illness.

Understanding the emotional responses to illness is crucial for improving patient care and support, as it directly influences patient outcomes and satisfaction. Recognizing and addressing patients' emotional reactions, such as fear, anger, sadness, joy, and compassion, can enhance the provider-patient relationship and facilitate better health outcomes (Naidorf (2024), Beale (2017). By recognizing patients' emotions, addressing their concerns, and involving them in treatment decisions, healthcare providers can enhance patient outcomes and create a more compassionate and collaborative healthcare environment (Naidorf, 2024). Emotional responses can profoundly influence a patient's capacity to understand and act on health information, frequently posing obstacles to accessing healthcare services (Beale, 2017). Integrating technology, including intelligent support systems and biofeedback sensors, offers valuable tools for evaluating and managing patients' emotional states, delivering emotional support and practical assistance in their daily lives (Maj et al., (2024), Wilson et al. (2016). The system will facilitate communication between patients and doctors, allowing for preliminary diagnoses and tailored treatment plans based on collected data. It will also provide patients with health reports and treatment recommendations to aid their recovery (Maj et al., 2024). Moreover, incorporating psychotherapeutic teaching into medical education can enhance communication skills among healthcare providers, enabling them to understand better and address the emotional aspects of illness (Groves, 2015). Emotional support is vital to patient satisfaction but is frequently underemphasized in healthcare settings. By recognizing and implementing practical strategies for providing emotional support, healthcare organizations can enhance patient satisfaction and elevate the overall quality of care. (Adamson et al., 2012)

Moreover, the emotional impact of illness and care, particularly in chronic conditions like advanced kidney disease, emphasizes the need for healthcare providers to acknowledge and address patients' emotional experiences. Neglecting these aspects can foster mistrust and isolation, adversely affecting the care experience (O'Hare et al., 2018). Patients often struggle with feelings of personal responsibility for their illness, commonly blaming themselves for their kidney disease and believing it was preventable. This tendency toward self-blame underscores the importance of healthcare providers addressing the emotional dimensions of chronic illness to enhance overall patient care and support (O'Hare et al., 2018). Illness requires adaptations in communication and roles, making effective management and open dialogue essential for sustaining and strengthening relationships in the face of challenges associated with chronic and mental health conditions (Bute et al., 2007). A comprehensive understanding of patients' emotional responses to illness can lead to more effective, empathetic, and patient-centered care, ultimately enhancing the healing process and patient satisfaction (Picton, 2011). Addressing and understanding the emotional aspects of illness are crucial for improving patient care and satisfaction. By incorporating empathy, clear communication, innovative technologies, and comprehensive provider training, healthcare systems can develop a more compassionate, patient-focused approach that fully acknowledges the emotional impact of illness. This approach enhances the provider-patient relationship, supports better health outcomes, builds trust, and elevates the overall quality of care.

Economic impact

The economic impact of illness is multifaceted, affecting individuals, households, and broader economies in various ways. Mental health illnesses, for instance, impose a significant economic burden, as evidenced by studies from countries like Canada, where costs are projected to increase six-fold over the next 30 years, potentially exceeding A$2.8 trillion (Doran & Kinchin, 2017). In Nigeria, mental health issues are prevalent and pose a threat to economic stability without robust policy interventions (Owoeye, 2024).

Chronic illnesses also have profound economic implications, particularly in low- and middle-income countries. In Nigeria, chronic illnesses lead to substantial direct and indirect costs, with many households spending over 10% of their income on health, often resorting to borrowing or selling assets to cope (Okediji et al., 2017).

Similarly, catastrophic health expenditures in Korea are rising, especially among low-income groups, highlighting the inadequacy of current health safety nets. Despite universal health coverage in Thailand, severe illness significantly increases out-of-pocket expenses and reduces household labor income by nearly a third, forcing reliance on informal financial support (Neelsen et al., 2015). The impact of illness on employment is also notable; in Australia, illness-related early retirement results in significant income loss, increased government support payments, and reduced tax revenue, amounting to billions annually (Schofield et al., 2011). In rural India, adult illness reduces workforce participation and earnings, though households attempt to mitigate these effects through increased labor participation by non-sick members (Alam et al., 2018). Furthermore, illnesses like hypercholesterolemia contribute to the economic burden of cardiovascular diseases, with direct costs ranging significantly, underscoring the need for updated research and public health strategies (Ferrara et al., 2021). Overall, the economic impact of illness is substantial, necessitating comprehensive policy responses to mitigate these effects and support affected individuals and economies.

Mental health illnesses contribute significantly to the economic burden across various countries, impacting both direct and indirect costs. In South America, mental health conditions, along with other noncommunicable diseases, are projected to cost approximately 7.3trillion from 2020 to 2050, equating to about 47.3 trillion from 2020 to 2050, equating to about 42.5 trillion, with indirect costs, such as lost productivity, being particularly substantial (Ferranna et al., 2023). In developed countries, mental health issues account for around 4% of GDP, with significant productivity losses, as mental illness is prevalent among working-age populations (Frank, (2022), Doran & Kinchin (2020)). In Canada, the economic costs of mental illness are expected to increase six-fold over the next 30 years, highlighting the growing financial impact (Layard, 2016). In Germany, mental illnesses accounted for societal costs of 146 billion euros in 2015, representing 4.8% of GDP, with a significant portion attributed to direct health costs (Doran & Kinchin, 2017). The economic burden is not limited to direct healthcare expenses but extends to lost productivity, social exclusion, and reduced educational attainment, which are common across various regions, including Europe and Nigeria (Lambert et al., (2023), Agboola et al. (2018)). Mental disorders such as depression, anxiety, and schizophrenia are particularly burdensome, necessitating increased investments in mental health care and cost-effective interventions to mitigate these impacts (Turk & Albreht, 2010). The economic implications of mental health are profound, affecting individuals, families, and national economies, and underscore the need for comprehensive policy responses to address these challenges effectively (Razzouk, 2017).

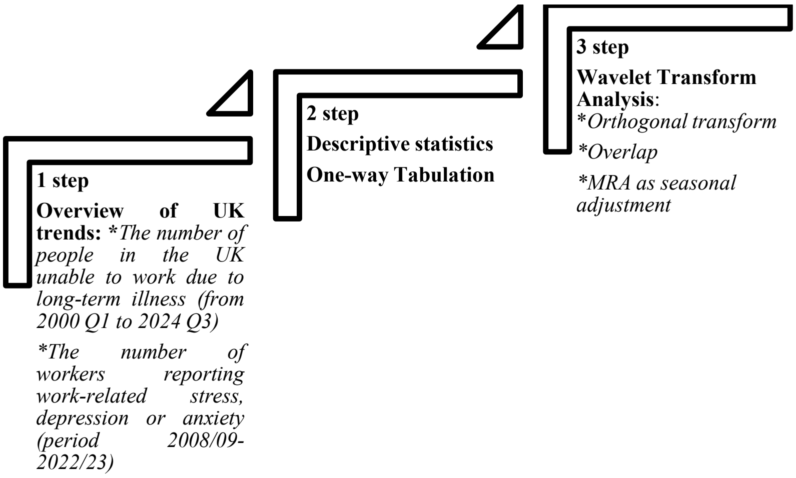
The economic costs associated with mental health illnesses are substantial and multifaceted, encompassing both direct and indirect expenses across various countries. Direct costs primarily include healthcare expenditures such as hospital stays, medication, and therapy, which in Germany alone amounted to 44.4 billion euros in 2015, representing a significant portion of the country's GDP (Lambert et al., 2023). Indirect costs, however, often surpass direct costs and include loss of productivity, unemployment, and social exclusion, which collectively contribute to a global financial burden estimated at 2.5 trillion annually, projected to rise to 2.5 trillion annually, projected to rise to 6 trillion by 2030 (Frank (2022), Sowers et al. (2019)). In the United States, mental illnesses affect about 20% of the population, with social costs growing more rapidly than healthcare costs, highlighting the broader societal impact (R. Frank & Glied, 2023). In South America, the macroeconomic burden of noncommunicable diseases, including mental health conditions, is estimated to reduce GDP by about 4% over the period from 2020 to 2050 (Ferranna et al., 2023) (Ferranna et al., 2023). The indirect costs are further exacerbated by factors such as poverty, low educational levels, and gender inequity, which are prevalent in many regions (Razzouk, 2017). In Nigeria, the economic burden on households is significant, with many individuals unable to afford even essential goods due to the high costs associated with managing mental illnesses (Agboola et al., 2018). These costs burden individuals, families, and national economies, necessitating increased investments in mental health care and implementing cost-effective interventions to mitigate these impacts (Razzouk (2017), Martini & Attallah (2019). The complexity of estimating these costs is compounded by variations in definitions, populations studied, and incomplete data, yet improved methodologies are helping to provide a clearer picture of the economic impact of mental disorders (Trautmann et al., 2016). Overall, the economic costs of mental health illnesses are profound, affecting not just healthcare systems but also the broader economic and social fabric of societies worldwide.

METHODOLOGY

The methodologies used to estimate the economic burden of mental health illnesses vary significantly across different regions, reflecting diverse approaches and challenges. One common method is the human capital approach, which considers both direct costs, such as healthcare expenses, and indirect costs, including productivity losses due to disability or death (Frank, 2022). This approach is complemented by the value of the statistical life (VSL) method, which assesses the economic impact of mental health by evaluating trade-offs between risks and capital, similar to methods used for other major diseases like cardiovascular conditions (Frank, 2022). In Canada, a comprehensive measure of the economic burden incorporates medical resource use, productivity losses, and reductions in health-related quality of life (HRQOL), highlighting the significant role of indirect costs (Lim et al., 2008). The economic evaluation frameworks often used in these studies include cost-of-illness studies, which are crucial for informing resource allocation decisions by comparing costs and outcomes to assess efficiency (Patel, 2018). However, these evaluations face methodological challenges, such as determining the appropriate perspective (e.g., societal or health service) and the measurement of costs and outcomes, with debates surrounding the use of quality-adjusted life years (QALYs) in mental health studies (McCrone, 2011). In Europe, the economic burden of mental disorders like depression is primarily driven by indirect costs, such as productivity losses, which account for a significant portion of the total costs. Variations in definitions further compound the complexity of estimating these costs, populations studied, and cost components, necessitating more standardized approaches to achieve consensus (Jacobs et al., 2018). Additionally, the multidisciplinary nature of mental health interventions requires consideration of diverse cost categories, including social care, informal care, and education, which are often impacted by mental health issues (Shearer et al., 2016). Overall, while methodologies differ, there is a consensus on the substantial economic burden posed by mental health illnesses, underscoring the need for improved methods and increased investment in mental health care (Razzouk, 2017), Trautmann et al. (2016)).

Our research design is placed in Figure 1.

Figure 1. *Methodological framework*



Source: Done by authors

Wavelet transforms are typically categorized into two main types:

1. Continuous Wavelet Transform (CWT): Provides a highly detailed time-frequency representation by continuously scaling and shifting the wavelet. The results are often visualized as a scalogram, which shows the signal's energy distribution across time and scales (Mallat (1999), Torrence & Compo (1998)).

2. Discrete Wavelet Transform (DWT): Uses discrete scales and translations for computational efficiency, making it widely used in practical applications like signal denoising and compression.

Advantages of Wavelet Transform Analysis

- Time-Frequency Localization: Captures transient features and patterns that occur only at specific times.
- Multiscale Analysis: Decomposes signals into components at different resolutions, allowing simultaneous analysis of global trends and local details.
- Noise Robustness: Effectively separates noise from meaningful signal components, enhancing data interpretability (Mallat, 1999).

Wavelet Transform Analysis is a robust mathematical technique used to decompose a signal into components localized in both time and frequency domains. Unlike Fourier analysis, which provides a global frequency representation, wavelet analysis can reveal transient and time-varying features within a signal. This makes it particularly useful for analyzing non-stationary data across various scientific and engineering domains. Wavelet analysis usually consists of transforms, variance decomposition, thresholding, and outlier detection.

RESULTS AND DISCUSSION:

Overview of the UK situation.

For our analysis, we have taken the UK as a case because in this country people unable to work due to long-term illness peaked a lot. Overall, it is estimated that nearly one-fifth of the UK's working-age population has a condition that limits their ability to work. The think tank suggests that this issue has grown so severe that it now poses a significant threat to the country's economic potential.

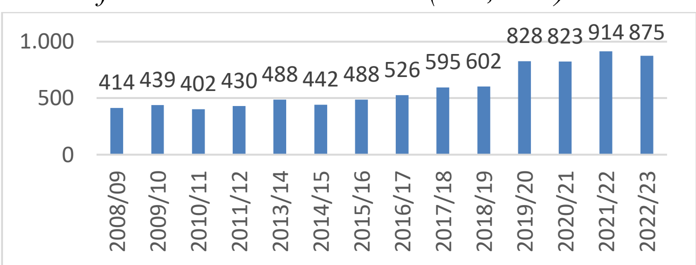
In early 2024, the number of people in the UK unable to work due to long-term illness peaked at 2.82 million, though this figure declined slightly in subsequent months. This marks a significant rise from just over 2 million in 2019. Before 2022, the previous high of 2.38 million occurred in late 2021 and early 2022. At that time, caregiving for family members was the leading cause of inactivity. Since late 2021, however, long-term and temporary illnesses have become the dominant factors, comprising 32.2% of the economically inactive population by Q3 2024.

Figure 2. *The number of people in the UK unable to work due to long-term illness*

Source: Done by authors using data from Statista

The reasons behind this increase remain uncertain if we want to focus on the causes of rising long-term illness. As of 2022, mental health conditions were the leading causes, with 313,000 citing mental illness and 282,000 naming depression-related issues. The COVID-19 pandemic also likely played a role; in April 2022, 1.8 million people reported experiencing Long Covid. While long-term sickness remains most prevalent among those over 50, younger groups have seen notable increases. Between 2019 and 2022, the number of individuals aged 16–34 on long-term sick leave rose by 140,000, compared to a 32,000 increase for those aged 35–49. The UK labor market has remained tight in recent years, favoring job seekers. In 2022, unemployment hit its lowest level since the 1970s, with job vacancies peaking at 1.3 million in May. Although wage growth was robust during this time, high inflation led to real-term pay reductions between late 2021 and mid-2023. By December 2023, redundancies reached their highest levels since April 2021 at 116,000, signaling potential cooling in 2024. Despite this, the labor market remains resilient by historical standards.

Figure 3. *Number of workers reporting work-related stress, depression or anxiety in Great Britain from 2008/09 to 2022/23 (in 1,000s)*



Source: Done by authors using data from Statista

From 2008/09 to 2022/23, the number of workers in Great Britain reporting work-related stress, depression, or anxiety has shown a significant upward trend. In 2008/09, approximately 415,000 workers reported such conditions. This figure increased over the years, reaching around 602,000 in 2014/15. A notable rise occurred during the COVID-19 pandemic, with reports peaking at approximately 914,000 in 2021/22. In 2022/23, the number slightly decreased to about 875,000 workers. These statistics underscore the escalating concern of work-related mental health issues in the UK workforce over the past decade and a half.

Descriptive Statistics and One Way Tabulation

We start our quantitative analysis by calculating the main descriptive statistics parameters. Analyzing the data from 2000 Q1 until 2024 Q3, we can see that the maximum number of economically inactive people due to long-term sickness in the United Kingdom was at the highest level in 2024 Q1 and reached 2 820 (in 1,000s) while the quarterly average was 2227,404 (more data of descriptive statistics in Table 1).

Table 1. *Results of Descriptive Statistics.*

Mean	2227,404
Median	2209
Maximum	2820
Minimum	1959
Std. Dev.	198,3388
Skewness	1,30528
Kurtosis	4,730509
Jarque-Bera	40,46496
Probabibility	0
Observations	99

Source: Done by authors using Eviews and data from Statista

The descriptive statistics provide an overview of the patterns and characteristics of economically inactive individuals due to long-term sickness, offering insights into the UK's health and labor market challenges. The data reveals trends, variability, and anomalies that are critical for understanding the broader socio-economic implications.

The mean value of 2227.404 thousand people represents the average number of economically inactive individuals due to long-term sickness per quarter across the dataset. The median value of 2209 thousand people is slightly below the mean, indicating that the dataset includes some higher values (outliers) that increase the mean. This reflects periods where sickness-related inactivity spiked, likely during major health crises or demographic shifts. The dataset spans from a minimum of 1959 thousand people to a maximum of 2820 thousand people, a range of 861 thousand. This range highlights the variability in inactivity levels over time, likely influenced by underlying factors such as chronic illness prevalence, healthcare accessibility, demographic trends, and external shocks like the COVID-19 pandemic.

The standard deviation of 198.34 thousand people reflects moderate variation around the mean, indicating that while inactivity levels were generally consistent, there were notable fluctuations during the observed period. The positive skewness of 1.30528 suggests that the distribution is right-skewed, with a few quarters experiencing significantly higher levels of inactivity. This likely reflects acute events, such as pandemics or systemic health crises. The kurtosis value of 4.730509 indicates a leptokurtic distribution, with a sharper peak and heavier tails than a normal distribution. This suggests that while most observations are close to the mean, extreme values (outliers) are more common than in a normal distribution. The Jarque-Bera test statistic of 40.46496 with a probability of 0 indicates a significant departure from normality. This non-normality can be attributed to the presence of outliers, skewness, and kurtosis in the dataset. With 99 observations, the dataset covers a substantial period, likely capturing long-term trends and episodic events affecting economic inactivity.

The distribution indicates a relatively stable baseline of economically inactive individuals due to long-term sickness, with the mean and median close in value. However, the positive skew and leptokurtic nature suggest the influence of episodic events, such as the COVID-19 pandemic, that temporarily elevated inactivity levels. The variability in the data highlights the dual challenge for policymakers: addressing the steady baseline of long-term sickness through healthcare improvements and chronic disease management while preparing for and mitigating the impact of acute health crises. The high mean value reflects a significant and persistent economic burden on the labor market and public resources. This underscores the need for targeted interventions to reduce long-term sickness-related inactivity, including preventive healthcare, workplace accommodations, and mental health support programs.

The data's non-normal distribution and right skew call for further investigation into the drivers of extreme values. Time-series methods, such as wavelet analysis, could be employed to identify periodicity, trends, and the impact of specific events (e.g., pandemic waves, policy changes). The descriptive statistics highlight the substantial and variable burden of long-term sickness on economic inactivity in the UK. The findings emphasize the importance of sustained efforts to improve public health infrastructure and resilience, addressing both chronic and acute factors influencing labor market participation.

In the next step, we will conduct a one-way tabulation, which offers a detailed dataset summary by presenting the frequency distribution of a single variable. This analysis is particularly useful for understanding data distribution, as it helps identify how data points are spread across different categories or values. It also assists in detecting outliers by spotting values that occur infrequently, which may indicate anomalies. The results of a one-way tabulation can be found in Table 2.

Table 2. *Results of One Way Tabulation.*

Value	*Count*	*Percent*	*Cumulative count*	*Cumulative Percent*
[1800,2000)	*8*	*8,08*	*8*	*8,08*
[2000,2200)	*38*	*38,38*	*46*	*46,46*
[2200,2400)	*44*	*44,44*	*90*	*90,91*
[2400,2600)	*1*	*1,01*	*91*	*91,92*
[2600,2800)	*5*	*5,05*	*96*	*96,97*
[2800,3000)	*3*	*3,03*	*99*	*100,00*
Total	*99*	*100,00*	*99*	*100,00*

Source: Done by authors using Eviews and data from Statista

Based on the results in Table 2 the tabulated results provide a detailed distribution of the quarterly number of economically inactive individuals due to long-term sickness, highlighting both the concentration and variability within the dataset. This analysis is critical for understanding patterns and trends in economic inactivity caused by health conditions. The majority of observations (82.82%) fall within the [2000,2400) range, with the [2200,2400) category being the most prevalent (44.44%). This concentration indicates that, over the observed period, the typical number of inactive individuals remained relatively stable. The lower range [1800,2000) accounts for only 8.08%, suggesting that values below 2000 were rare, potentially reflective of either improved health or a smaller affected population in earlier years. The upper ranges [2400,2600), [2600,2800), and [2800,3000) collectively represent 9.09% of the dataset. These values likely correspond to significant disruptions, such as the COVID-19 pandemic that temporarily increased long-term sickness rates.

The scarcity of values in the [2400,2600) (1.01%) and [2800,3000) (3.03%) ranges highlights that deviations from the central trend, whether due to health improvements or crises, were limited in duration and frequency. By the [2200,2400) range, the cumulative percentage reaches 90.91%, indicating that most periods were characterized by relatively moderate levels of long-term sickness-related inactivity. This suggests that fluctuations occurred but were generally confined to predictable limits. The clustering of data within the [2000,2400) range reflects temporal stability in the number of individuals inactive due to sickness, which may align with long-term trends in chronic illness prevalence, healthcare access, and demographic factors. The relatively few observations in higher ranges, especially [2800,3000), may signify the influence of significant but short-lived events like the COVID-19 pandemic, which temporarily elevated inactivity rates. This finding highlights the importance of monitoring and mitigating such disruptions. The relatively consistent mid-range values suggest that targeted policies to improve healthcare access and manage chronic conditions could significantly reduce the burden of long-term sickness. However, the occurrence of high-end values underscores the need for preparedness to address unexpected health crises that can strain the labor market.

In conclusion, this distribution analysis provides valuable insights into the dynamics of long-term sickness-related economic inactivity in the UK. It underscores the importance of a dual approach: addressing the steady baseline of chronic illness while preparing for and mitigating the effects of health crises on the labor force.

Wavelet Transform Analysis

Wavelet analysis typically begins with a wavelet transform of the time series of interest, a process conceptually similar to a Fourier transform. In this step, the time series is broken down into its spectral (frequency) components across different scales. In wavelet analysis, the concept of scale is analogous to frequency in Fourier analysis. This process re-expresses the time series data from its time-domain representation to its frequency-domain behavior. This transformation helps identify the signal's activity's most prominent scales (or frequencies).

We made Wavelet Transform Analysis based on decomposition: Orthogonal transform –DWT, filter class – Haar. Wavelet transform analysis can be practically applied to study the number of economically inactive people due to long-term sickness by examining how the patterns and trends in this data evolve over time, particularly when complex, non-stationary factors like economic conditions, health crises, or policy changes influence these patterns.

Figure 4. *Wavelet transform analysis: Orthogonal transform*

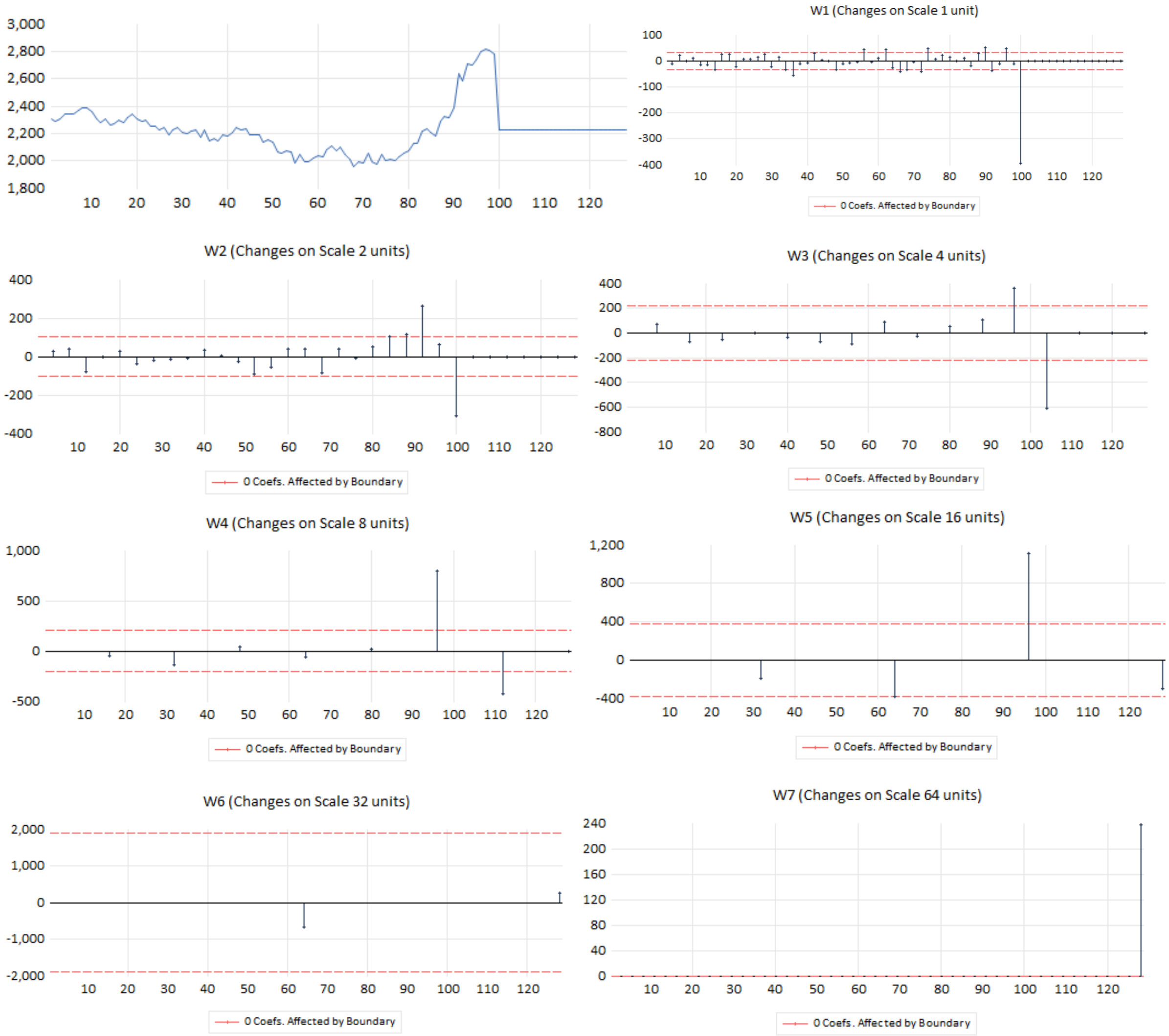
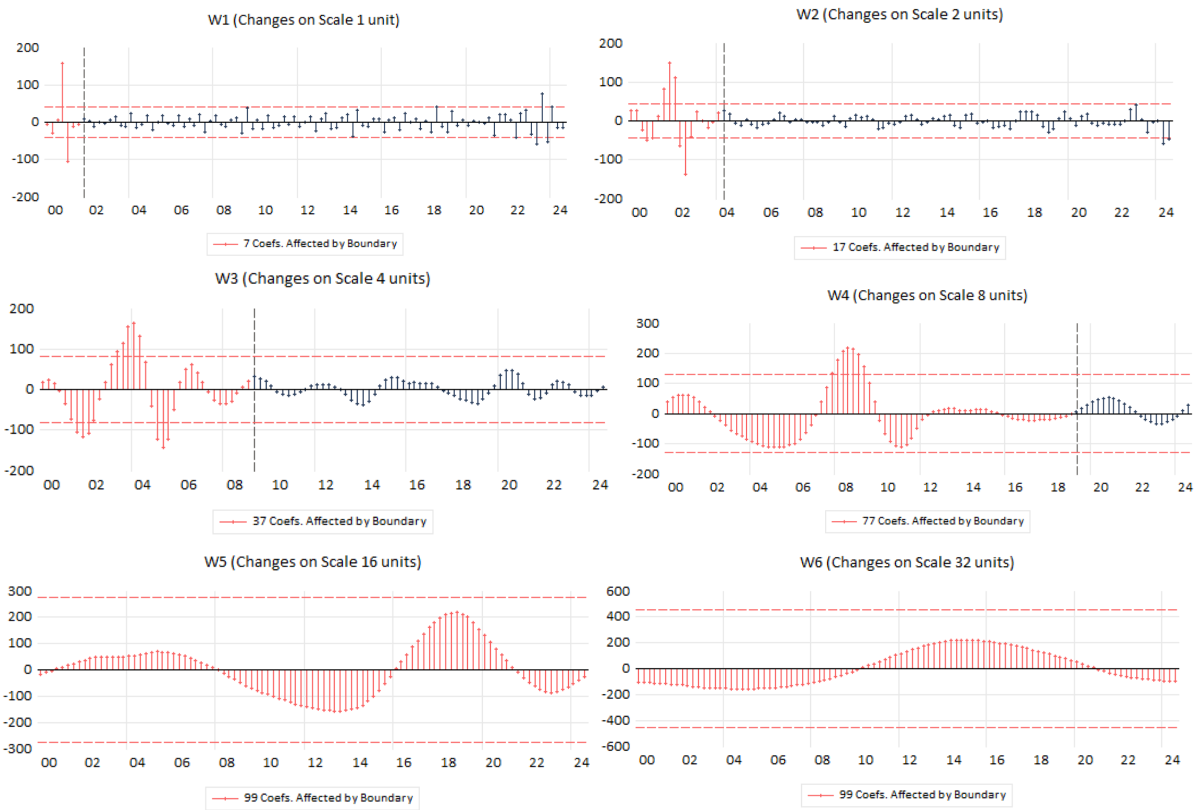


Figure 4. indicates a summary of the wavelet transformation performed. The first plot in the output is a plot of the original series and the padded values in case a dyadic adjustment was applied. The last 7 plots are, respectively, the wavelet coefficients. At the first scale of wavelet decomposition, the frequency spectrum is effectively divided into two equal parts: low and high-frequency components. The low-frequency portion corresponds to the scaling coefficients (VV), while the high-frequency portion corresponds to the wavelet coefficients (WW). Notably, the spectra associated with the wavelet coefficients are significantly less pronounced than those of the scaling coefficients, suggesting that the number of economically inactive people due to long-term sickness in the United Kingdom series may be non-stationary.

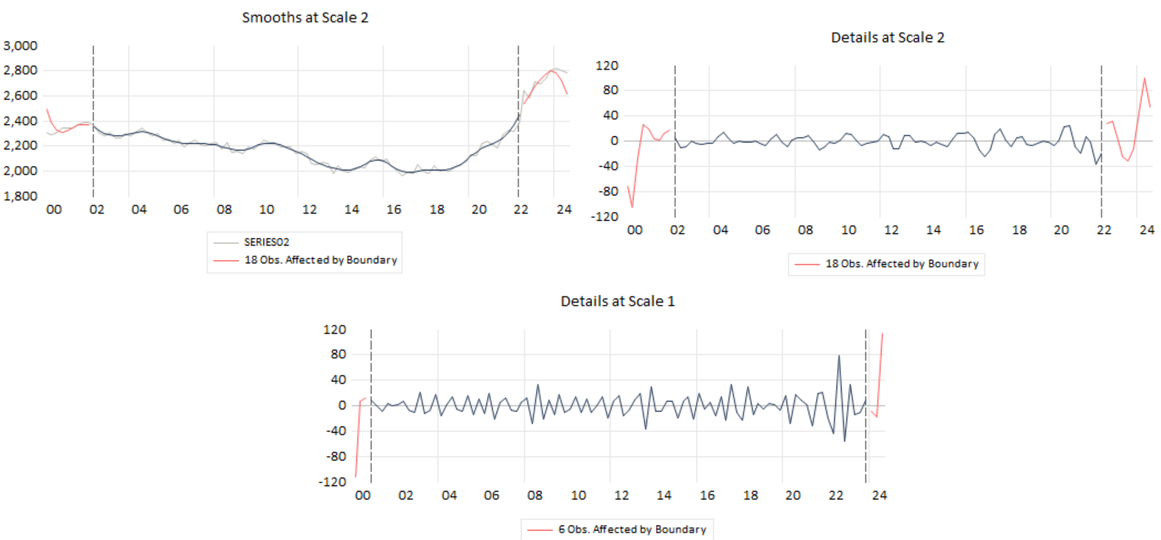
Additionally, the wavelet plot includes two dashed red lines, which denote the ±1 standard deviation range for the coefficients at that scale. This visualization aids in identifying wavelet coefficients that should be shrunk to zero as part of wavelet shrinkage applications, highlighting the insignificant coefficients. Coefficients that exceed a specific threshold—here, the standard deviation—are retained, while the rest are shrunk to zero. From this, it becomes clear that most wavelet coefficients at scale 1 can be disregarded, providing further evidence that high-frequency components in the number of economically inactive people due to long-term sickness in the United Kingdom series are not prominent.

Figure 5. *Wavelet transform analysis: Overlap*



Although wavelet decomposition is not a formal statistical test, it provides an excellent method for identifying which scales (or frequencies) dominate the behavior of the underlying series. This analysis is not restricted to the first scale. To illustrate this, we will repeat the abovementioned process using the maximum overlap discrete wavelet transform (MODWT) with the Daubechies (daublet) filter of length 6. The transform will be applied up to the maximum possible scale, indicating which and how many wavelet coefficients are influenced by boundary conditions.

Figure 6. *Wavelet transform analysis: MRA as seasonal adjustment*



Wavelet analysis helps identify patterns and uncover trends in long-term sickness-related inactivity (e.g., seasonal effects, economic cycles). The results reveal that certain times of the year show spikes in inactivity due to sickness, which may be linked to flu seasons or other health-related phenomena. From our analysis, we see that the COVID-19 pandemic had a huge impact on UK number of economically inactive people due to long-term sickness. At the same time, we see a significant change in the number of workers reporting work-related stress, depression or anxiety in the UK. By analyzing low-frequency components, wavelet transforms identify broader trends, such as a gradual increase or decrease in long-term sickness rates over decades, potentially linked to aging populations or healthcare accessibility. Analyzing short-term fluctuations, high-frequency components are used to detect abrupt changes, such as those caused by significant events (e.g., a pandemic, economic downturns, or policy changes like stricter sick leave regulations). Wavelet-based models help forecast future inactivity rates by understanding past patterns, aiding policymakers and healthcare providers in preparing for potential increases in long-term sickness. Our results show that the level after the COVID-19 pandemic has changed significantly and can affect future trends considerably. It is essential to initiate changes in social security or healthcare policies which can help to create shifts in inactivity rates. Wavelet analysis can help pinpoint when these changes occurred and assess their immediate and long-term effects.

The main findings of this research identify that an increase in economically inactive people due to long-term sickness over the last years from 2020 can be due to aging populations or chronic diseases; extreme weather conditions, which can be related to climate change challenges, but the most probable is the COVID-19 pandemic highlighting the need for targeted healthcare interventions. On the other side, we think that one of the reasons, but not the main factor, can be the attitude towards sickness, which has changed after the COVID-19 pandemic because, before it, many people continued working even after being sick. By understanding these dynamics, policymakers can design better health and labor policies, allocate resources more effectively, and implement preventive measures to mitigate future risks associated with long-term sickness and economic inactivity. The UK must take serious decisions to manage this problem as it can start affecting economic trends and increase health problems.

CONCLUSIONS

The UK has witnessed a substantial rise in the number of economically inactive individuals due to long-term sickness, with the highest levels recorded in early 2024. This increase, from approximately 2 million in 2019 to over 2.8 million in 2024, highlights a pressing issue affecting the nation's workforce. The trend suggests that a combination of factors, including aging populations and the increasing prevalence of chronic diseases, drive this growth. Notably, the data indicates a demographic shift in long-term sickness, with younger populations also exhibiting higher rates of inactivity. This phenomenon underscores the need for comprehensive health monitoring systems and proactive intervention strategies to manage the impacts of these changes on economic productivity. Wavelet transform analysis was instrumental in decomposing the time-series data of economically inactive individuals, revealing complex, multi-scale patterns of change over time. This method effectively captured short-term fluctuations linked to transient factors such as seasonal health issues and acute economic disruptions by isolating high-frequency components. Simultaneously, low-frequency components illustrated the underlying long-term trends, enabling a clearer understanding of persistent factors like chronic illnesses and systemic changes in health and labor market conditions. This dual analysis provided nuanced insights, allowing policymakers and researchers to identify the causes of sickness-related inactivity and the optimal time frames for implementing policy interventions.

The COVID-19 pandemic was a significant catalyst for the rise in long-term sickness rates, with lasting repercussions beyond the immediate health crisis. The pandemic's direct impacts, such as Long COVID symptoms affecting an estimated 1.8 million people in April 2022, compounded pre-existing health challenges. Moreover, the pandemic induced broader societal shifts, including heightened awareness and sensitivity toward illness and a greater propensity for individuals to prioritize health over economic activity. This marked change in attitudes likely contributed to a reduction in the normalization of working while unwell, suggesting that COVID-19 has permanently altered societal and workplace norms regarding health and productivity.

Mental health conditions have emerged as a leading cause of long-term sickness-related economic inactivity, particularly among younger demographics. Between 2019 and 2022, individuals aged 16–34 reported a sharp increase in mental health-related sickness, reflecting a growing vulnerability among younger workers to conditions such as anxiety, depression, and work-related stress. This trend aligns with broader findings that mental health challenges have surged globally, fueled by post-pandemic recovery pressures, economic uncertainty, and workplace burnout. These findings underscore the urgency of integrating mental health support into employment policies, including initiatives for stress management, flexible working conditions, and workplace mental health programs, to prevent further deterioration of the labor force's well-being. The rising levels of long-term sickness-related economic inactivity present a critical challenge to the UK's economic potential. A smaller active labor force, increased healthcare expenditures, and social security demands could constrain economic growth. Policymakers must prioritize investments in healthcare infrastructure and social safety nets to address the root causes of long-term sickness. Simultaneously, labor market policies should incentivize businesses to adopt flexible and inclusive employment practices, enabling individuals with chronic or mental health conditions to remain economically active. Addressing these challenges will require cross-sector collaboration, integrating healthcare, social policy, and economic strategies to mitigate the adverse effects of long-term illness on both individuals and the broader economy.

Wavelet-based models demonstrated their utility as a forecasting tool, highlighting both immediate and long-term trends in sickness-related inactivity. By analyzing historical patterns, these models can predict future surges in inactivity rates, aiding in strategic resource allocation. For example, the models identified the COVID-19 pandemic as a pivotal event that disrupted historical trends and set a new trajectory for inactivity levels. Policymakers can use these insights to anticipate potential shocks, such as future pandemics or climate-related health crises, and proactively design interventions to reduce their impact. This approach ensures public health and economic resilience by enabling a rapid, informed response to emerging challenges.

To develop effective solutions for the rising rates of long-term sickness, further research must explore the interplay between various contributing factors, including demographic shifts, climate change, mental health, and socioeconomic conditions. Longitudinal studies could provide deeper insights into how these elements interact and evolve over time. Additionally, a focus on regional disparities and vulnerable populations would ensure that policies address the specific needs of diverse groups. Policymakers should emphasize preventive healthcare measures, such as regular health screenings, mental health education, and community-based wellness programs, to reduce the incidence of long-term sickness. Furthermore, economic policies must consider the financial implications of inactivity and incentivize businesses to proactively support employee health and well-being.

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