Nonfarm Employment's Impact on U.S. GDP And Policy Optimization

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Abstract. This research reveals a robust, real-time correlation between U.S. nonfarm payroll employment and short-run economic output. It subsequently uses this connection to obtain useful information for nowcasting and policy assessment. Monthly PAYEMS data and quarterly nonfarm GDP value added (GVA) data are the two main official data series used in this analysis. The analysis synchronizes their frequencies, calculates growth rates, and investigates the employment-output relationship in both levels and growth terms. A linear fit in levels shows that there is a strong, near-unitary long-term relationship between nonfarm employment and GVA. In terms of growth, a parsimonious contemporaneous regression with an elasticity of about 4–5 explains approximately half of the variation in quarterly GVA. This means that a 1% increase in payroll growth corresponds to about 4–5% more GVA growth in the same quarter. Rolling 20-quarter estimates and a crisis-interaction demonstrate evident state dependence: the elasticity decreases by approximately one quarter during the 2008–2009 and 2020 shock periods but subsequently re-establishes itself within its historical range. Based on these results, this paper suggests an operational two-regime rule-of-thumb: during normal periods, convert payroll data to GVA utilizing the baseline elasticity with explicit uncertainty bands; during stress regimes, reduce the significance of the mapping and augment with other coincident indicators. Policy guidance follows the same logic: in normal times, raise the average returns of jobs to value added through ICT and human-capital upgrades; in crises, preserve viable matches with work-sharing and targeted wage support while allowing reallocation. This framework transforms a widely recognized labor statistic into a transparent, actionable tool for policy-making, business planning, and investment decisions.

Keywords: Nonfarm Payroll Employment (PAYEMS); Employment-Output Elasticity; State-Dependent Dynamics; Nowcasting; Rolling-Window Regression.

1. Introduction

1.1. Research Background:

Nonfarm payroll employment (NFP) is the most closely monitored indicator of U.S. labor-market conditions because it counts wage-and-salary jobs across nearly all private and public industries outside of farming, as produced by the Bureau of Labor Statistics' Current Employment Statistics (CES) program [1]. According to the Federal Reserve's (FRED) records of the PAYEMS series, about 80% of the workers who add to GDP are not farmers. This is the reason why changes in payrolls and changes in total output are so closely related [2]. Gross domestic product (GDP), the broadest indicator of the nation's economic health, is defined by the Bureau of Economic Analysis as the market value of all finished goods and services produced in the United States. In accordance with national accounting standards, this study concentrates on gross value added (GVA) in the nonfarm business sector, excluding government and housing expenses [3].

There are three main practical reasons why it is important to examine how changes in NFP affect GDP. In order to improve nowcasts and risk monitoring in between BEA releases, it first offers a high-frequency window on quarterly growth. Second, it assists in measuring the employment-output elasticity that supports decisions about monetary, labor-market, and fiscal policy (e.g., the number of nonfarm jobs linked to a one percentage-point change in real GDP growth). Third, an employment-to-GDP mapping can help policymakers come up with targeted policies that maximize output while avoiding overheating or labor shortages. This is due to the fact that the reallocation of sectors, automation, and demographic trends all have a direct impact on payroll.

1.2. Literature Review

Employment is a concurrent indicator of real economic activity, as confirmed by extensive business cycle measurement. Stock and Watson's composite-index framework quantified how employment helps track output fluctuations in real time, and current institutional practice reflects this logic: The Conference Board's U.S [4]. Coincident Economic Index lists payroll employment as one of its four core components, alongside income, sales, and industrial production [5]. At the macro-relationship level, the classic link between output growth and labor-market conditions—Okun's Law—has been shown to remain strong and reasonably stable across advanced economies and decades, reinforcing the premise that movements in labor utilization carry systematic information about aggregate output [6].

Building on this foundation, recent research shifts attention from unemployment rates to employment levels and asks whether nonfarm payrolls (NFP) add predictive value for GDP. Salisu's analysis of data from 1947 to 2021 reveals that U.S. nonfarm payroll (NFP) contains out-of-sample information relevant to U.S. output growth when models accommodate asymmetries and structural changes—demonstrating that payroll releases improve real-time GDP tracking beyond basic benchmarks [7]. The Chicago Fed demonstrates that at more granular geographic levels, state nonfarm payroll employment is a key indicator of regional economic activity, and that explicit modeling revisions enhance real-time evaluation [8]. These strands collectively advocate for the consideration of NFP as a high-frequency, policy-relevant indicator for quarterly GDP, while integrating regime shifts and data-revision dynamics into empirical frameworks. This consensus on the informational value of NFP, however, has not yet converged on a standardized, direct estimate of the structural elasticity that links quarterly NFP changes to output in a transparent framework.

1.3. Research Gap

Most prior studies have concentrated on unemployment-based relationships, such as Okun's Law, or on the financial market responses to the monthly payroll report, but few papers have provided a direct quantification of the structural elasticity from nonfarm employment (NFP) to real GDP at the quarterly level. Moreover, existing literature often relies on mixed-frequency econometrics or high-frequency event studies, which may obscure the underlying employment–output mechanism. Consequently, a clear, interpretable estimate of the core structural parameter—the elasticity of output with respect to employment—remains elusive for policymakers and forecasters.

This paper addresses this gap by employing a transparent and tractable approach: By using only two core macroeconomic series—nonfarm payroll employment (PAYEMS) and nonfarm business gross value added (GVA)—this study aligns their frequencies at the quarterly horizon. By transforming both log levels and growth rates, the employment-to-output elasticity is directly estimated, and its stability is validated over time using rolling regressions and crisis-period interactions. This simple but effective design avoids overfitting, highlights the structural link between labor input and output, and provides a clear empirical basis for forecasting and policy analysis.

1.4. Research Framework

To address these gaps, this study implements a three-stage empirical framework designed to directly estimate and validate the NFP-to-GDP elasticity: First, a diagnostic scatter of employment growth against nonfarm GVA growth is presented to establish the empirical link that motivates the modeling. The positive fitted slope and tight cloud justify treating GVA growth as a function of employment growth. Log-growth transformations are used, extreme tails are winsorized in sensitivity checks, and monthly payrolls are converted to a quarterly series (with robustness to end-of-quarter sampling versus quarterly averaging) in order to avoid leverage from crisis quarters.

Second, the relationship is examined over time through a rolling 20-quarter OLS of GVA growth on employment growth. The elasticity's time-path changes during expansions, weakens during supply-driven events, and spikes during the pandemic. This shows that you shouldn't assume that the parameters stay the same. Accordingly, this rolling profile is both proof of structural change and a goal that our simple model should follow at medium horizons while filtering out short-term noise.

Third, the predictive usefulness is assessed in a pseudo-real-time exercise. Each quarter is nowcast using only the information available up to that date, and fitted values from the employment-based regression are overlaid on actual GVA growth. Benchmarking is conducted against naive and autoregressive alternatives, and the residuals are examined to identify periods of shock sensitivity and asymmetric responses.

Subsequent to these procedures, the employment-to-output elasticity is documented. Historical decompositions from the rolling regressions are employed to ascertain the factors influencing employment fluctuations, and the estimates are transformed into a straightforward scenario tool that illustrates how monthly job variations (for instance, ±250k) might impact quarterly output results. Robustness checks are conducted across subsamples, including pre/post-2000 and pre/post-2020. Alternative seasonal adjustments are also considered. In addition, hours and earnings are included to test for omitted variable bias. These steps ensure that the estimated elasticity is not an artifact of a specific time period, seasonal adjustment method, or missing variables. The results ultimately confirm the stability and practical relevance of the findings.

2. Method

This study utilizes two primary datasets, both sourced from the U.S. Bureau of Labor Statistics and retrieved from the Federal Reserve Bank of St. Louis's FRED repository. The first dataset uses the total number of nonfarm payroll employees in the United States from January 1939 to July 2025 as the initial data. The data is collected every month, and the unit is in thousands [2]. The second dataset uses the value added by the nonfarm business sector in the United States from January 1947 to April 2025 as the initial data. The data is collected every three months, and the unit is millions [3]. After preliminary data validation and verification, neither dataset had any missing values. First, this paper preprocesses the datasets by making sure that the two datasets have consistent frequency. This is achieved by converting the frequency of the PAYEMS dataset to quarterly intervals. Merge the quarterly PAYEMS data PAYEMS with the quarterly GVA data. This consolidation makes sure that both datasets have the same frequency, which makes it easier to compare and analyze. For analytical purposes, this paper uses the log-level to show long-term relationships and the log-difference to mitigate the interference caused by non-stationarity.

To analyze the dynamic relationship between labor input and economic output, this study constructed two key growth rate variables: The quarterly growth rate of nonfarm employment is denoted as GEM, reflecting the relative change in nonfarm employment between two consecutive quarters. The quarterly growth rate of nonfarm GDP value added is denoted as GVA, indicating the percentage increase in annual GDP value added if the growth rate for that quarter were sustained throughout the year. Thus, GEM captures the quarterly dynamics of employment scale, while GVA measures the quarterly annualized growth of nonfarm sector output. Together, they reflect the short-term linkage between labor input and economic output.

To quantify the fundamental relationship between employment growth and output growth, this study specified a linear regression model. Next, this paper establishes a linear regression model. The independent variable is the quarterly growth rate of nonfarm employment, while the dependent variable is the quarterly annualized growth rate of nonfarm GDP. The model is expressed as: $GVA = \alpha + \beta * GEM + \varepsilon$. Here, β represents that for every 1 percentage point increase in the employment growth rate, the annualized growth rate of nonfarm GDP increases by an average of β percentage points. To assess the temporal stability of the employment-output elasticity and to test for structural breaks during major economic crises, this paper implemented two additional empirical strategies. Then, this paper employs a rolling regression approach to examine the stability of the relationship between employment and GDP. Using 20-quarter samples sequentially, it dynamically estimates the elasticity of employment growth with respect to GDP growth and charts its trajectory over time. Furthermore, a crisis interaction term model is specified to capture the impact of the 2008–2009 financial crisis and the 2020 pandemic on the coefficients. ggva = α + β1*GEM + β2*Crisis + β3(GEM * Crisis) + ε. Here, β1 represents the employment-output elasticity during normal periods, β2 denotes the additional fixed effect during crises, and β3 measures the change in this elasticity during crisis periods. Finally, this paper compares actual and employment-based fitted GVA growth to evaluate how much of quarterly output dynamics can be captured by payrolls alone.

3. Empirical Results: The Dynamic Link Between Employment and Output Growth

This study's analysis reveals four key findings: (1) a remarkably stable long-run level relationship between employment and output; (2) significant short-to-medium-run fluctuations in the employment-output elasticity, captured by rolling regressions; (3) a statistically significant weakening of this elasticity during major economic crises; and (4) the strong contemporaneous predictive power of payroll growth for output growth in normal times.

3.1. Strong Long-Run Linear Relationship

This paper first uses linear regression to show the long-term relationship between nonfarm employment and GVA. The regression results and scatter plot indicate a strong long-term relationship between nonfarm employment and nonfarm business GVA. According to R Studio results, the regression model formula is GVA = (-5.621e+03) + (1.312e-01) * GVE. The estimated coefficient for employment is highly significant, indicating that for every 1,000 additional workers, GVA increases by approximately $131 million. Figure 1 reveals a very close, monotonically increasing relationship between nonfarm employment and nonfarm business GVA. This trend corresponds with the calculated coefficients. The relationship appears largely linear across mid-range levels of employment but displays slight convexity at the upper end, where recent years lie above the fitted line. This suggests that in larger economies, each additional worker is associated with greater value added, a pattern consistent with capital deepening and productivity improvements. The high R-squared value, which is equal to 0.9316, shows that the model explains over 93% of the variation in GVA, confirming a tight linkage between the two variables. The correlation coefficient r = 0.9652 further confirms a strong linear relationship.

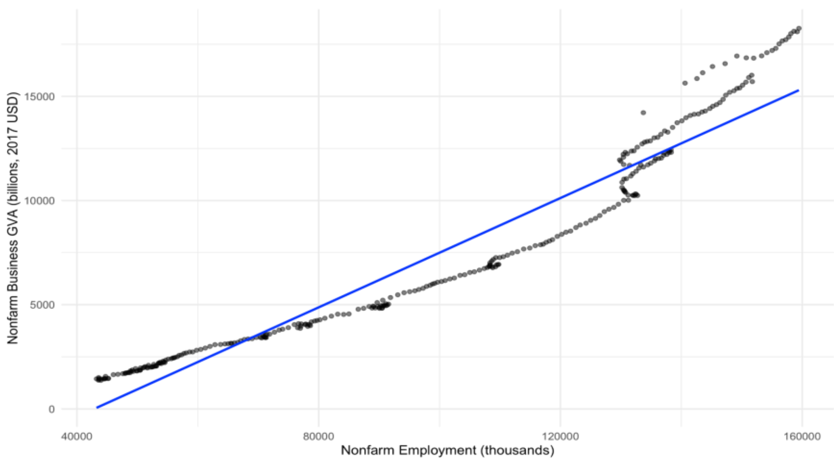

Fig. 1 Long-Run Relationship Between Nonfarm Employment and GVA

A stable long-term relationship between employment and nonfarm GVA aligns with national accounts principles. Value added is defined as gross output minus intermediate inputs. Therefore, when the economy employs more labor together with capital and technology, total value added tends to increase in proportion [9]. Over long horizons, labor and capital usually move in tandem with trend productivity. This co-movement produces the strong level fit observed in the estimates. At higher employment levels, the slope's steepening is consistent with rising output per worker. Three mechanisms explain this: capital deepening, which raises the marginal product of labor, multifactor productivity (MFP) gains from technology and reallocation, and gradual improvements in labor quality [10]. Evidence from the U.S. ICT diffusion era shows that IT investment and use accelerated capital deepening and raised productivity broadly, amplifying value added at scale [11].

Urban and market-size effects also matter. Large, diversified labor markets foster spillovers, better input matching, and tougher competition, all of which increase productivity and make the employment-GVA relation more convex in high-employment states [12]. Finally, since both series trend, validating a true equilibrium relation requires cointegration tests; a stable error-correction mechanism would confirm that deviations are temporary rather than spurious [13].

3.2. 20-Quarter Rolling Estimates

This paper continuously estimates the relationship GVA = $\alpha + \beta$ * GEM using a 20-quarter rolling window. The resulting coefficient β is plotted as a time series to observe whether this relationship changes with economic conditions. Results show β remained stable at 3–6 for most periods, with temporary increases in the early 1980s, 1999–2001, and 2017–2019 (periods associated with economic booms and productivity surges). It plunged significantly to near 0–2 during the 2008–2009 financial crisis and briefly turned negative with sharp volatility in 2020 (periods marking severe economic contractions); Post-pandemic, the curve has re-established itself around 4–5, indicating that the relationship has largely returned to normal, as shown in Figure 2.

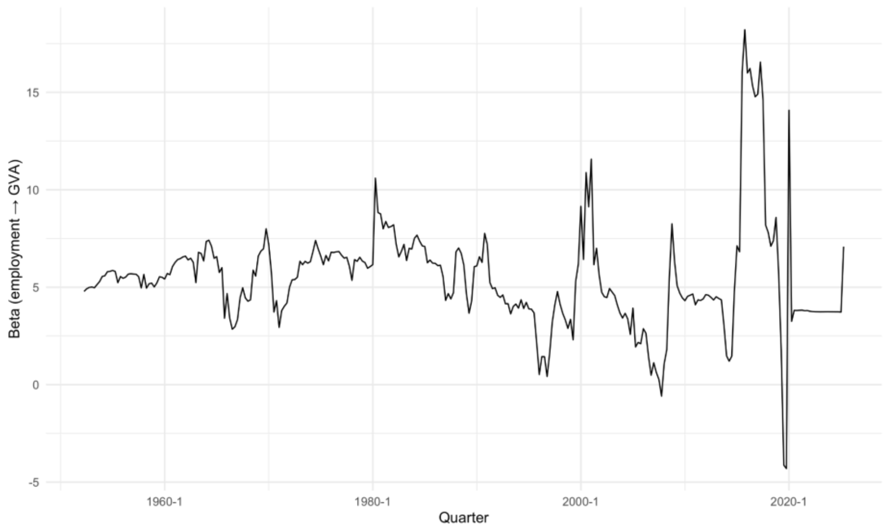

Fig. 2 Rolling 20-Quarter Employment Elasticity

The rolling 20-quarter elasticity between employment and GVA captures how the strength of the relationship evolves with economic conditions. For much of the postwar period, the elasticity fluctuates around 3–6, indicating that increases in employment were consistently associated with proportionate gains in output. This stability aligns with Okun's Law, which highlights a persistent link between labor-market activity and aggregate output [14].

Periods of temporary surges, such as the early 1980s and late 1990s, reflect cyclical booms when productivity growth was elevated—driven by capital deepening and the spread of information technology [15]. Conversely, the collapse of elasticity to near zero during the 2008–2009 crisis illustrates how financial disruptions can sever the normal transmission from jobs to output: firms may hoard labor or cut hours instead of reducing headcount, weakening the employment–output link [12].

The sharp volatility around 2020, including negative values, reflects the unique pandemic shock, where mandated shutdowns and rapid reopenings distorted both employment and measured output simultaneously [16]. Post-pandemic, the elasticity has re-stabilized around 4–5, suggesting that the structural relationship has largely returned to its historical range. This highlights the resilience of the employment–output nexus despite severe disruptions.

3.3. State-Dependent Employment–Output Elasticity

Using a crisis interaction, this paper finds a strong state dependence in the employment-to-output mapping. To quantify whether the employment–output link weakens in downturns, this study estimates GVA=α+β1*GEM+β2*Crisis+β3*(GEM*Crisis)+ε, where the crisis period from the third quarter of 2008 to the fourth quarter of 2009 and from the first quarter of 2020 to the third quarter of 2020 is set to 1. The results indicate that the normal time elasticity is b_1≈5.26. This implies that for every 1 percentage point increase in the nonfarm payroll employment growth rate, the annualized growth rate of total nonfarm value added during the same period will increase by approximately 5.26 percentage points. The interaction term $b_3 \approx -1.30$ is negative and significant. This implies that during the crisis window, elasticity declines to $b_1+b_3 \approx 3.95$, indicating that the transmission of employment to output weakens by approximately 25%. Model fit is meaningful for quarterly macro data (Adjusted R-squared≈0.56; residual standard error ≈3.89), and the joint F-test is highly significant ($p<2.2e-16$).

The crisis-interaction model confirms that the employment–output elasticity is state dependent, weakening substantially during downturns. In normal times, a 1 percentage point increase in nonfarm payroll growth translates into roughly a 5.3 percentage point increase in GVA growth, consistent with the long-run elasticity estimates. However, during the 2008–2009 financial crisis and the 2020 pandemic, the elasticity declined by nearly 25%, reflecting the severe disruptions to normal labor–output transmission. Research on the Great Recession documents that many firms engaged in labor hoarding, keeping workers on payroll despite reduced output, which lowered measured employment–output elasticity [12]. Similarly, during COVID-19, sudden shutdowns and reopening shocks caused sharp output swings unmatched by equivalent employment adjustments, as payroll support policies temporarily muted job losses [16].

The results are also consistent with broader evidence that elasticities vary across the cycle: Okun's Law tends to flatten in recessions when unemployment is sticky downward and when employers reduce hours instead of cutting jobs [14]. Moreover, countercyclical productivity movements amplify this effect—output per worker often falls less than proportionally during contractions due to compositional shifts [17]. Taken together, the interaction term results highlight that crises fundamentally alter labor–output dynamics, but once extraordinary conditions subside, the elasticity reverts to its historical range.

3.4. Nowcasting Nonfarm GVA with Payroll Growth:

Figure 3 plots actual nonfarm GVA growth against the fitted values from a contemporaneous growth regression, gva=α+β*GEM+ε, estimated on the full sample. The model yields α^=1.51 and β^=4.33, meaning that in a quarter with flat payrolls the economy still grows about +1.5 pp on average, and that a 1-pp increase in nonfarm payroll growth is associated with roughly +4.3 pp higher annualized nonfarm GVA growth in the same quarter. Visually, the dashed predictions track the solid actual series closely through most post-war expansions and mild slowdowns, confirming that payrolls are a high-information coincident signal for quarterly output. The conspicuous gaps cluster in severe stress episodes—most notably 2008–09 and 2020—when labor hoarding, hours/intensity adjustments, shutdowns, and timing frictions temporarily weaken the headcount-to-output mapping, producing short-lived over- or undershoots. Fit is strong for quarterly macro data: R square=0.55, so payrolls explain about half of the variation in GVA growth. The residual standard error is 3.94 pp, giving the typical one-quarter miss in annualized percentage points; residuals range from −16.0 to +14.8 pp, with the largest gaps clustered in stress episodes (e.g., 2008–09, 2020). Economically, this validates using $\beta \approx 4–5$ as a normal-times conversion from jobs growth to output growth; in crises, as shown by your interaction model, the elasticity drops, and the mapping should be down-weighted.

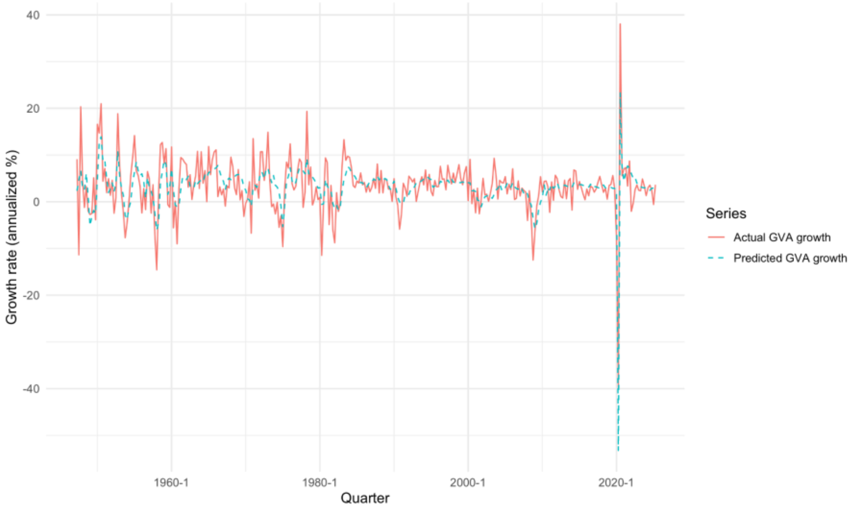

Fig. 3 Actual vs. Predicted Nonfarm GVA Growth

The comparison between actual and predicted GVA growth shows that payroll employment is a high-information coincident indicator for quarterly output. The fitted values track the actual series closely across most postwar expansions and slowdowns, with an average elasticity of around 4–5. This validates the economic logic that jobs and output move together at high frequency, echoing the broader evidence on the reliability of coincident indicators in business cycle monitoring [4].

The largest gaps appear during systemic stress episodes such as the 2008–2009 financial crisis and the 2020 pandemic, when payrolls failed to capture abrupt swings in measured output. In the Great Recession, widespread labor hoarding and hours adjustments weakened the headcount-to-output mapping, reducing model accuracy [12]. In 2020, sudden shutdowns and reopenings, combined with fiscal payroll support, produced large transitory deviations, as output collapsed and recovered more abruptly than employment [18].

Despite these episodes, the model explains over half of the variation in quarterly GVA growth, with residuals generally small outside crises. Economically, this suggests that a baseline elasticity of 4–5 can be used to translate payroll changes into output growth under normal conditions, while policymakers should down-weight this mapping during crises when timing frictions and policy interventions distort the relationship.

4. Discussion

4.1. Toward a Regime-Aware Framework for Dynamic Elasticity

Rolling estimates show that the relationship between employment and output is always changing. During normal times, it goes up and down around a baseline of 3 to 6. When productivity is high, the elasticity increases, but when supply or financial shocks happen, it decreases. Because of this change over time, both economic monitoring and policy design need to take into account the regime. First, time-varying or state-dependent filters should be used in real-time surveillance. For example, rolling regressions with break tests or updates that work like Kalman filters. These methods help turn payroll signals into predictions of growth. They are still in line with the empirical strength of Okun-type relationships, but they allow for coefficient variability. Second, reform packages that make workers more productive can increase elasticity. Investing in ICT, improving the people who work for the company, and upgrading human capital are some of the main factors. These things together push the elasticity toward the top of its historical range [12,19]. Third, firm-level practice can stabilize the mapping by prioritizing hours reallocation, cross-training, and re-skilling over separations when demand softens, preserving matches and lowering subsequent hiring frictions. Finally, the release of a quarterly elasticity tracker (with methodology and backtests) makes it more obvious how jobs are turned into output, which helps with budget planning and communicating with investors. This transparency not only makes policies more believable, but it also gives businesses and markets a shared way to make decisions and predictions. In short, it's important to be aware of cyclical changes and to put in place policies and metrics that focus on productivity. This will help improve the average returns of jobs compared to the value they add during times of growth. In summary, we know that things will change over time, but we should employ policies that focus on productivity and flexible measurement to make sure that jobs are more valuable during times of growth.

4.2. A Stabilization Toolkit for Crisis-State Dynamics

The imperative for a regime-aware approach becomes most acute during periods of systemic stress. During times of systemic stress, like the 2008–09 financial crisis or the 2020 pandemic, elasticity drops by about 25%. The reduction is due to labor hoarding, fewer hours, required shutdowns, and policy changes that change the usual reasons for hiring and firing. Stabilization should keep good matches while letting people switch jobs. Evidence supports the use of short-time work (STW) or work-sharing arrangements, along with targeted wage subsidies. Effective designs scale with hours reductions, require employer co-financing, and sunset automatically. Such measures have been shown to preserve jobs with limited deadweight loss when shocks are temporary [20,21]. Temporary payroll-tax holidays or hiring credits can ease cash-flow pressures and help small businesses avoid layoffs. At the same time, putting conditions like training plans or rehiring schedules on matches helps keep zombie matches to a minimum. These steps recognize that hoarding workers can change the way a crisis works [22]. Accordingly, policy should look for a balance. It needs to encourage productive hoarding that keeps good matches going during downturns, and it should also set up exit strategies that get rid of unproductive ones as the economy recovers. Income support should be combined with clear reopening protocols during health emergencies, as output can vary more significantly than employment. During these times, the payroll signal should carry less weight in real-time monitoring [17]. Ex-post, active labor-market policies that accelerate re-skilling and reallocation shorten the period of low elasticity. The overarching objective is to safeguard the transmission mechanism from jobs to output while circumventing misallocation that impedes recovery.

4.3. From Insight to Operation: A Two-Regime Rule-of-Thumb

Turning these insights into actionable guidance requires reducing them to a practical rule-of-thumb. Predicted-versus-actual comparisons show that payrolls are a high-information coincident indicator. Outside crises, the fitted paths explain a large share of quarterly GVA variation and suggest a conversion factor of about 4–5 from payroll growth (pp, annualized) to GVA growth. Operations should institutionalize a two-regime rule-of-thumb. Normally, a transparent nowcast that multiplies the most recent growth rate by the baseline elasticity is fed by monthly payroll releases; uncertainty bands represent revision risk and sampling error. According to the composite-indicator practice in business-cycle measurement, automatic triggers (such as credit spreads and large hours decline) change to a down-weighted mapping during stressful periods and are supplemented with additional coincident inputs, such as income, sales, and industrial production [5]. In order for job growth to more effectively translate into value added, investors should allocate their funds to sectors and regions with stronger productivity fundamentals. For businesses and HR, capacity planning should tie hiring and average hours to the two-regime signal. Publishing methodology and backtests increases accountability and prepares the payroll signal for decision-making in corporate planning, international capital, and policy.

5. Conclusion

This research demonstrates a strong and economically significant correlation between nonfarm employment and nonfarm GDP value-added. At this level, nonfarm employment and nonfarm GVA have a relationship that is almost positive and linear, which means that an average of approximately \$131k in annualized value is added per additional job. A simple contemporaneous model shows that the elasticity of quarterly growth is about 4–5, which means that a 1-pp rise in payroll growth leads to a 4–5 pp rise in annualized GVA in the same quarter and explains about half of the short-run variation. Rolling estimates place the elasticity mostly in the 3–6 range, rising in productivity booms and weakening in shocks; a crisis interaction confirms a ~25% drop (≈5.3 → ≈3.9) in 2008–09 and 2020 before re-anchoring near 4–5. These results underpin a two-regime rule-of-thumb: applying a conversion factor of 4–5 during normal periods and deliberately down-weighting this mapping during crises, complemented by indicators such as hours worked, compositional data, and other coincident metrics.

The contributions of this research are both methodological and practical, offering significant operational and policy relevance. For nowcasting, the employment mapping—grounded in transparent assumptions—provides a simple, real-time proxy for quarterly output, explaining approximately half of its short-run variance. For businesses and investors, it translates headline job gains into point estimates for sales and production—by applying the elasticity to payroll growth data—thereby improving planning, inventory, and risk management. For policymakers, the elasticity converts job-creation targets into implied growth outcomes and supports scenario analysis.

The model is intentionally parsimonious: it omits factors such as hours, earnings, productivity shocks, and financial conditions, which can be influential, particularly during crises. The omission of these variables means the estimated elasticity represents a reduced-form relationship that may vary if these omitted factors were accounted for. Quarterly aggregation may mask intra-quarter timing differences between payrolls and value added, and parameter stability could be affected by structural change. Future work should (i) incorporate hours and simple productivity proxies, (ii) test robustness with mixed-frequency or distributed-lag specifications, (iii) evaluate real-time vintage data, and (iv) examine sectoral heterogeneity. Collectively, these avenues for future work aim to enhance the model's robustness, real-time applicability, and granularity. Even with these caveats, the evidence strongly supports payroll employment as a reliable, easy-to-use lens on near-term output.

Authors Contribution

All the authors contributed equally and their names were listed in alphabetical order.

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