A Vector Autoregression Model for Depicting the Relation Between Labour Market Economic Indicators and Real Wages in the United States Manufacturing Sector

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Abstract: In recent years, the US manufacturing sector and its labour market dynamics have gained importance in the face of resurgent protectionism and increased governmental strategic investment plans. Simultaneously, real wage growth in the manufacturing sector has diverged compared to the wider economy. While studies have previously analysed the relationship between labour market conditions and real wages in the wider economy, few have specifically evaluated the manufacturing sector in this respect. To this end, we selected a comprehensive list of economic indicators covering the key aspects of the sectoral labour market. Subsequently, a vector autoregression (VAR) model was developed, enabling us to account for time lags and the interconnectedness of each variable. In addition to this, graphs and plots were created to provide a visual understanding of the database, results, and labour market dynamics. The findings of our model suggest that the economic consensus on real wage determination in the wider economy also holds for the manufacturing sector. An important exception to this is the strongly negative relationship between the inflation rate and real wages.

1 INTRODUCTION

This paper examines how labour market conditions affect changes in real wages in the United States manufacturing sector between the years 2000 – 2024. To this end, a Vector Autoregression (VAR) model was developed using a dataset compiled from various U.S. government databases (Federal Reserve Economic Data , ; **?**). Moreover, tests were also conducted to ensure the data complied with the necessary conditions for VAR modelling.

The US manufacturing sector has recently gained in political significance, as reshoring and tariffs have become more frequent. While the share of overall employment in the manufacturing sector has fallen over the recent decades, its share of GDP has remained largely constant due to improvements in productivity (Baily and Bosworth, 2014). This means that the manufacturing sector has broadly maintained its economic relevance throughout this period.

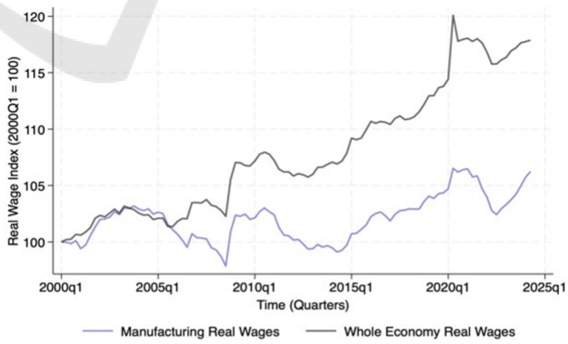

Figure 1: Time Series of Real Wages in the Manufacturing Sector against Real Wages in the Whole Economy.

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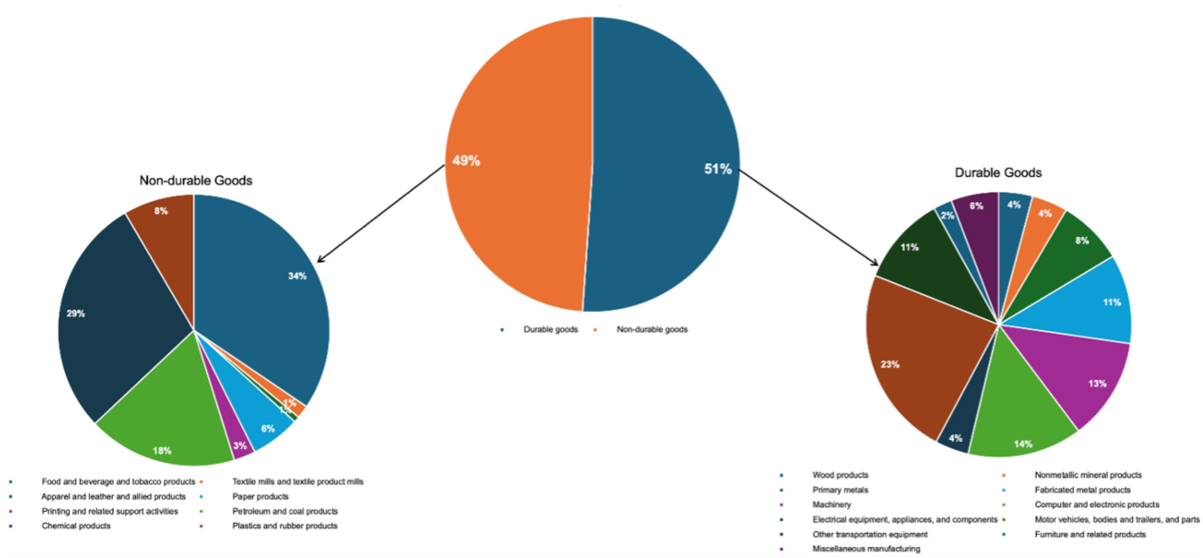

Figure 2: Time Series of Real Wages in the Manufacturing Sector against Real Wages in the Whole Economy.

Additionally, there has been a divergence between real wages in the manufacturing sector and those in the wider economy in recent decades (Figure 1). These factors motivate a fresh analysis of wage determination in the sector. Figure 2 provides insight regarding the composition of the US manufacturing sector. The industries shown are the subjects of analysis for this study.

The literary basis of our study will be further expanded in Section 2. Section 3 will outline the methodology, and the variables selected. Section 4 presents the results, visualisations and accompanying economic discussions followed by the conclusions.

2 LITERATURE REVIEW

The role of labour market variables as determinants of real wages has been widely discussed in economic literature. Domash and Summers (2022) utilised job openings and unemployment rates as indicators of slackness in the labour market, on the demand and supply side respectively. To further measure demand and supply side labour market forces, overtime hours and industrial production are considered. On the other hand, capacity utilisation has been employed by Stock and Watson (2020) to capture real cyclical economic activity.

A sectoral differentiation of wage determination has been previously studied by Sheffield (2013). They utilised a log-transformed linear regression model to analyse the impact of sector-specific market variables on real wage growth. The approach taken by Domash and Summers (2022) relies on various wage Phillips curve regressions at both the national and state levels in the US.

Another statistical model that has been utilised to analyse the effects of a variety of variables on real wage growth in the past is VAR. Bernanke and Blinder (1992) employ a VAR model to determine the effects of monetary policy on real wages. Similarly, Blanchard and Quah (1989) employ a structural VAR to analyse the effects of demand and supply shock on real wage growth. In both instances, analysis of the relationship between their chosen macroeconomic variables and real wage change. However, a VAR analysis of the manufacturing sector in the US has, to our knowledge, not been conducted before.

3 METHODOLOGY

This section describes the manufacturing sector's labour market variables for the study (Table 1). It also provides the specifications of the VAR model and the relevance of utilising VAR.

3.1 Dataset Details

This study uses a curated dataset utilising monthly data from December 2000 to May 2024 collected from the Bureau of Labour Statistics (BLS) (2024) and the Board of Governors of the Federal Reserve System via the Federal Reserve Economic Data (FRED) (2024) to analyse and examine the relationship between real wage change and various labour market economic indicators.

Table 1: Description of Variables.

Variable	Code	Unit
Year-on-year Change in Real Average Hourly Earnings of Production and Nonsupervisory Employees	RW	Percentage (%)
Avg. Weekly Overtime Hours of Production and Nonsupervisory Employees	WOH	Hours
Unemployment Rate – Private Wage and Salary Workers	UR	Percentage (%)
Job Openings (First Differenced)	JOB	Rate
Real Sectoral Output for All Workers	LP	Index (January 2017 = 100)
Capacity Utilisation (NAICS) Rate	CU	Percentage (%)
Industrial Production (NAICS)	IP	Index (January 2017 = 100)
Year-on-year Change in the Consumer Price Index (CPI) for All Urban Consumers: All Items in U.S. City Average (First Differenced)	INF	Percentage (%)

	WOH	UR	JOB	LP	CU	IP	INF
WOH	1						
UR	-0,5712	1					
JOB	0,0571	-0,4737	1				
LP	0,0177	0,0708	0,31	1			
CU	0,7365	-0,8334	0,4494	0,1401	1		
IP	0,6204	-0,6363	0,1628	0,3155	0,8611	1	
INF	-0,3193	-0,0381	0,2591	-0,163	-0,0844	-0,2715	1

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Figure 3: Correlation Matrix.

3.2 Vector Autoregression Model

This study employs a standard VAR model as proposed by Breitung and Hamilton (2020) of the following form as defined in Equation 1:

$$Y_t = c + \sum_{i=1}^{p} \phi_i Y_{t-i} + \varepsilon_t \qquad (1)$$

where:
Y_t: The $k \times 1$ vector of endogenous variables at time t.
c: The $k \times 1$ vector of constants.
ϕ_i: The $k \times k$ matrix of coefficients for the i-th lag.
ε_t: The $k \times 1$ vector of error terms at time t.
p: The number of lags in the model.
VAR models are effective at capturing the interconnectedness and the interdependent relationships among various variables. This is important considering the frequency of correlations in the dataset (Figure 3). VAR models enable an in- depth quantitative time-series analysis, which would be particularly useful to highlight the dynamic relationships among the multiple labour market time series variables. A 24-month lag was used to allow economic conditions to fully reflect on wages. Similar lags were estimated by Domash and Summers (2022).

Following the standard approach to VAR modelling, we tested for linearity, stationarity, interdependence of variables, lack of co-integration and sufficiently long time series. Our dataset contains monthly data for just under 24 years and includes 282 data points per variable, ensuring that the time-series is sufficiently long. Furthermore, stationarity was tested by conducting the 'Augmented Dickey–Fuller unit-root test', which determined that both the job openings rate and year-on-year inflation rate were non-stationary. To remedy this, a first-differenced transformation for these variables was undertaken, resulting in them becoming stationary. Moreover, the 'Johansen test for cointegration' and the 'LM test for

Table 2: Regression Results with Lagged Variables.

Variable	**Lag Month**	**Coefficient**	**Std. Error**	**z-value**	**p >z**	**95% Confidence Interval**
Unemployment Rate Sectoral	24	-0.0822	0.0317	-2.59	0.010	-1.4433 -0.02
Manufacturing Sector Labour Productivity	24	0.1484	0.0447	3.32	0.001	0.0608 0.2359
Industrial Production	24	1.2382	0.4125	3.00	0.003	0.4298 2.0466
(First Differenced) Job Openings Rate	24	0.3116	0.0792	3.94	—	0.1565 0.4668
Average Overtime Hours	24	-1.6491	0.2122	-7.77	0.000	-2.0649 -1.2332
YOY CPI (First Difference)	1	-0.7148	0.0964	-7.42	0.000	-0.9036 -0.5259
Capacity Utilisation Rate	24	-1.5795	0.5203	-3.04	0.002	-2.5992 -0.5597

residual autocorrelation' were conducted to ensure that there is no cointegration and no autocorrelation among selected variables. In addition, the 'Granger causality test' was conducted to check whether there is Granger Causation between year-on-year (YOY) change in real wages and the selected labour market variables. The results of all the Granger causality tests were significant, reflecting Granger causality between changes in real wages and our selected labour market indicators.

Additionally, we have employed a structural break from November 2008 to October 2009 which covers the period of volatility and instability during the financial crisis and shields our model from parameter instability at the time. The breakdown in the relationship between labour market variables over this time period, as evidenced by Michaillat and Saez (2019), is further supported by our structural break testing using the algorithm proposed by Bai and Perron (1998, 2003).

4 RESULTS AND DISCUSSIONS

The results from the vector autoregression are shown in the following Equation 2:

$$RW = -1.65WOH - 0.08UR + 0.31JOB + 0.15LP - 1.58CU + 1.24IP - 0.71INF + 128.43 \quad (2)$$

The coefficients above (Table 2) should be interpreted as follows: Unemployment rate sectoral indicates that a change in the rate of 1 percentage point is correlated with a fall of 0.0822 percentage points in the YOY change in Real Wages in the manufacturing sector after 24 months. The coefficients of the other variables can be interpreted in a similar way. The coefficient of variables for which the first difference was taken must be integrated upon interpretation. Figures 4 supplement the results by providing a more time sensitive dissection of variable comovements across the analysed period in the form of time series graphs plotting explanatory variables against YOY change in Real Wages.

This section will examine the results of the VAR model using economic theory. According to classical economic theory, real wage can be determined and affected by various factors such as bargaining power, an increase in demand for workers, productivity, an increase in the cost of living and inflation, etc. The variables selected in the VAR model seek to cover these wage-determining factors.

The negative relationship between the unemployment rate and real wages may be explained by a reduction in worker bargaining power caused by an increase in unemployment. As increases in jobseekers saturate the labour market, downward pressure is created on real wages (Figure 5). Notwithstanding, our model shows this negative relationship to be relatively weak. A potential explanation is that workers who have lost their jobs (and therefore their wages) are excluded from the average real wage calculation. If the group of workers which has become unemployed had lower wages than average, as was observed during the covid-19 pandemic (Bateman and Ross, 2021), then real wages would rise ceteris paribus. This may have partly offset the decrease in real wages due to lower worker bargaining power, making the coefficient for the impact of the unemployment rate on real wage relatively smaller than expected.

Similarly, an increase in real wages due to an increase in job openings can be justified due to an in-

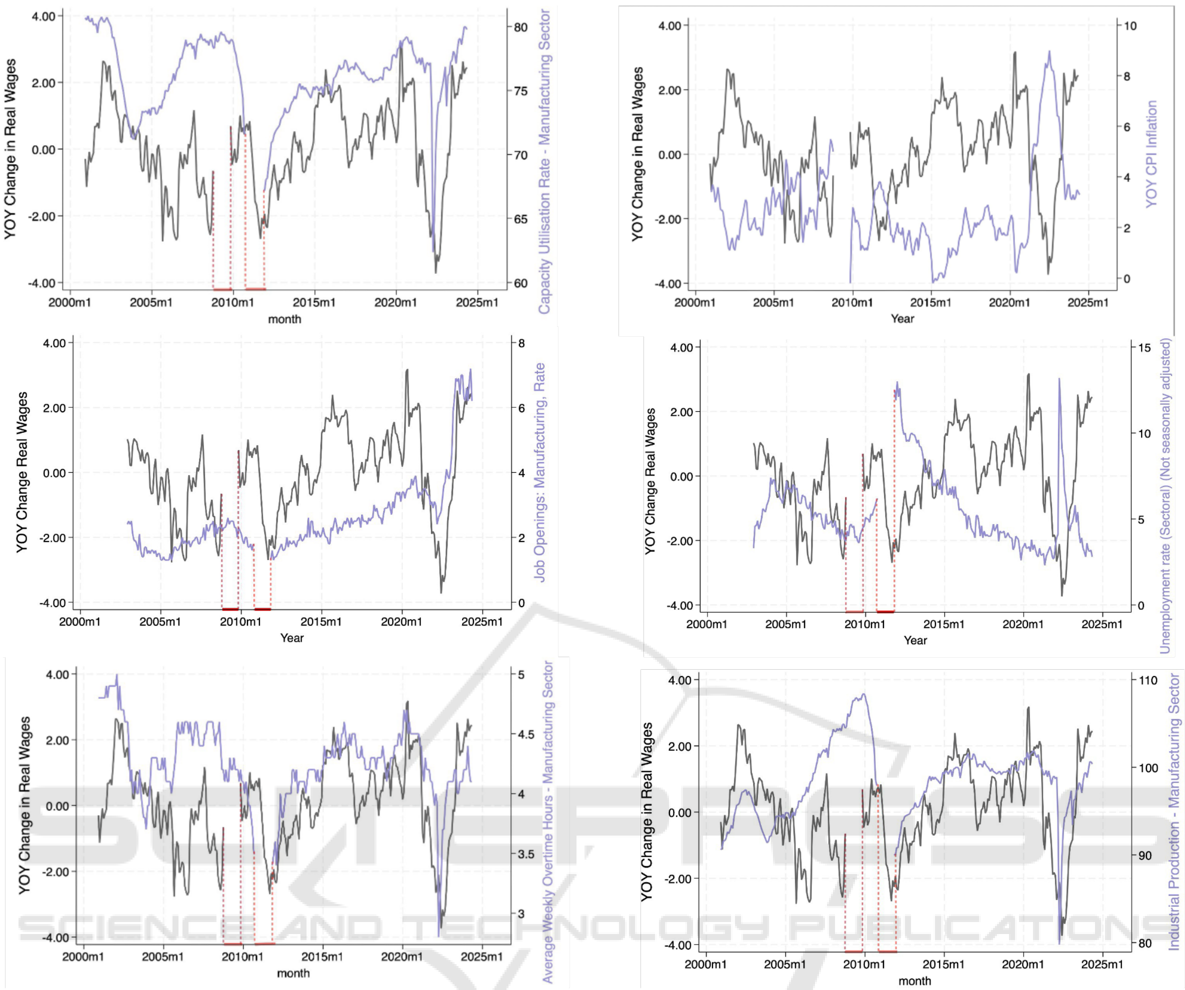

Figure 4: Time series graphs of lagged indicators with structural breaks.

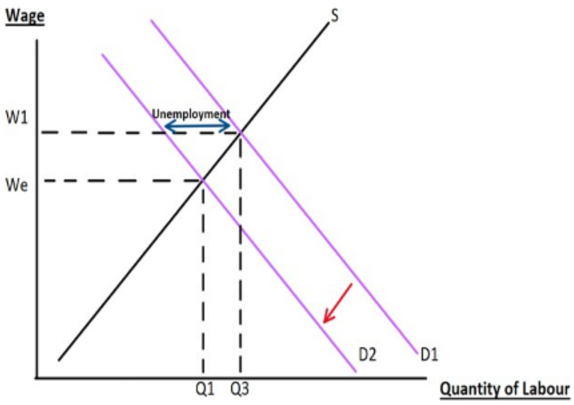

Figure 5: Effect of shift in demand for workers.

crease in demand for workers. Industrial production follows the same trend, given that increasing output tends to require an increase in workers operating at a firm. This creates a higher demand for workers, which increases their bargaining power and subsequently, their real wages. Figures 4c and 4f show that this link looks to remain resilient during times of crisis as can be seen in the coinciding shocks during the COVID-19 pandemic.

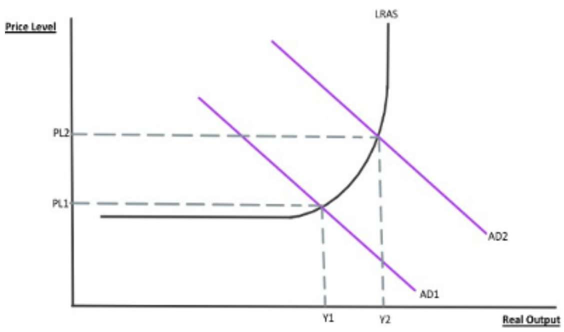

Figure 6: Effect of shift in demand for workers.

Another important factor that determines real wages is inflation or cost of living. Real wages are derived from the division of nominal wages by the infla-

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tion rate, commonly measured by the CPI, as shown below.

$$\text{RealWageRate} = \left(\frac{\text{NominalWageRate}}{\text{CPI}}\right) \times 100 \quad (3)$$

According to Equation 3, an increase in CPI leads to a fall in real wages, ceteris paribus. The negative CPI coefficient from our results implies that wages have not kept up with inflation over the analysed period. This phenomenon looks to be most apparent during the period of high inflation volatility of the early 2020s, which was mirrored by large swings in the YOY change of real wages (as observed in Figure 4d). This indicates that US manufacturing sector labour markets struggle to keep pace in uncertain inflationary environments. Further adding to the depressive effect on real wages is that inflation generally indicates economic instability, during which investments in the economy tend to fall as ROI (return on investment) becomes more uncertain and difficult to project.

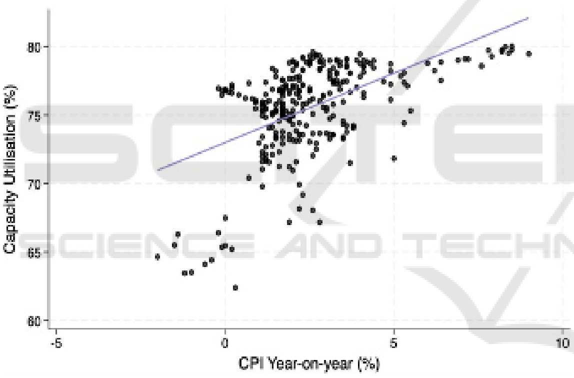

Figure 7: Effect of shift in demand for workers.

The strong negative relationship between average overtime hours and real wages evidenced by both the results from the VAR and the synchronous movement observed in Figure 4e, may be explained by workers choosing to increase their overtime hours during times of poor economic outlook and high cost of living in an effort to maintain their living standards (Ciphr, 2023).

The strongly negative coefficient of capacity utilisation follows orthodox Keynesian economic theory. As the economy approaches full capacity, an increase in aggregate demand leads to high inflationary pressure and a decreasing marginal increase in real output (represented in Figure 6). As previously discussed, real wages tend to fall under higher inflation. Hence, ceteris paribus, high-capacity utilisation creates inflationary pressure in an economy, hence lowering real wages as per Equation (3).

Empirically, the positive relationship between capacity utilisation and the inflation rate is shown by a correlation coefficient of 0.42 (See Figure 7).

5 CONCLUSIONS

This research study shows that labour market economic conditions are conducive to real wage changes in the United States' manufacturing sector between the years 2000 and 2024.

The study found that the two main factors affecting change in real wages are bargaining power and inflation. This is due to an increase in bargaining power affecting a worker's ability to negotiate a higher wage ceteris paribus. In addition, inflation reduces the real value of a worker's nominal wage, hence having a significant impact on their real wages. By developing a comprehensive VAR model, this study has displayed and quantified each lagged variables' effect on YOY change in real wages. The dataset and VAR model results have been presented using a variety of visualisation techniques, including time-series graphs, pie charts, a scatter plot and heat map. The results are also significant from a policy perspective. Inflation has been shown to be highly corrosive to real wages in the US manufacturing sector as labour markets have not exhibited sufficient flexibility to absorb the effects. While it is evident that policy makers ought to prioritise inflation stabilisation, the results from average overtime hours indicate that certain contractionary fiscal policies may not be effective in periods of economic overheating. For example, income taxation would not efficiently reduce aggregate demand (a key factor in the reduction of inflation) as the results suggest workers prefer to increase working hours rather than decreasing personal consumption.

The approach taken in this paper could be expanded to include other sectors or countries in future studies.

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