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The effect of real wages on productivity: evidence from dynamic panel models.

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Abstract

This study aims to add to the insufficient literature on the effect of real wages on productivity on a firm level. Using Compustat data of publicly listed firms in the US over the period 1950 to 2022, the magnitude of the effect of real wages on short-term productivity is studied using dynamic panel models. To study the effect of employee bargaining power on this effect, a distinction for knowledge intensive industries is made as a proxy. The study shows that there is a positive elasticity of real wages on productivity of 0.364 or 0.282 depending on the estimation of the total factor productivity, and that this effect is higher for firms in knowledge intensive industries compared to their non knowledge intensive counterparts. Compared to aggregated long-run studies, the results of this paper show significantly lower coefficients, indicating that there is rigidity in the effects. This suggests that short- and long run incentives regarding wage setting are different, which can have severe consequences on the management of a firm. As well as give insights to policy makers on what drives firms in their wage setting strategy.

Contents

Introduction

In terms of world economics, one word is especially relevant when describing the past 2 years: Inflation. Reaching over or close to double digits in most areas of the world and reaching levels that have not been seen since the period 1978-1982 (Romei & Smith, 2023). This has deteriorated real wages for the first time since 2008 (Foroohar, 2022). But over the same period, more than half of the price increases in the non-financial sector in the US can be attributed to an increase in profit margins (Bivens, 2022). This wage productivity gap or decoupling is a controversial topic within mainstream media and the field of economics.

Articles by the Economic Policy Institute (Bivens, 2022) and papers like Stansbury and Summers (2018) show a large productivity-pay gap. And this notion is also picked up by more mainstream media, where headlines like "Why the Gap Between Worker Pay and Productivity Is So Problematic" (White, 2015, Title) and "Why American wages haven't grown despite increases in productivity" (Picchi, 2021, Title) can be read. This gap can also be seen in action in multiple examples of businesses, one of which is UPS. UPS made record profits in 2022, but are currently under the threat of a potential strike, as union negotiations broke down (Isidore, 2023 ; Napolitano, 2023).

The usual focus in this conversation is on the worker, and therefore on the compensation of their productivity. But as total compensation is still one of the driving factors for retaining and attracting employees, and competition for talented workforce has heated up during the pandemic (De Smet et al., 2022), it is also important for firms to know what the effect is of the wages they pay on their productivity. As keeping wages low hurts a firms competitiveness in the labor market.

Additionally, as policymakers are tasked with difficult challenge of protecting the purchasing power of vulnerable groups, especially during times of high inflation. It is important for policymakers and unions to know what drives the wage decisions of firms. As this could assist in creating policy that is needed to protect workers' wages (OECD, 2018). This leads to the research question for this paper:

Do higher real wages cause an increase in firm-level productivity in the US?

This relationship has been studied before. And there is empirical evidence as well as theoretical arguments for why a positive relationship exists. Alfred Marshall in the late 19th century was the first to describe that fair wages could increase efficiency in the workplace. Akerlof & Yellen (1986) later modernized these theories and argued that paying employees above market rates could benefit firms even if that would mean higher employee costs.

Within long run cointegrated vector autoregressive (VAR) models, Tsionas (2003) studies the relationship on a country level in Europe. And argues that higher real wages increase the opportunity cost of labor, which can stimulate effort and therefore productivity. Other research using similar methodologies study the relationship within different manufacturing industries (Strauss & Wohar, 2004 ; Kumar et al. 2012). Fuss & Wintr (2008) study the relationship on a firm-level by using a dynamic panel model, but do so in the direction of productivity on real wages. This paper adds to the literature of using dynamic panel models to study the effect of real wages on productivity on a firm-level.

Literature review:

The relationship between real wages and productivity has been studied many times before. The different directions of the relationship have been evaluated using many different types of datasets as well as statistical methods. The most important findings will be discussed in this section.

Real wage and productivity decoupling

There is much discussion on the connection between wages and productivity as these factors were strongly linked in the US up until 1973, after which they started to diverge (Stansbury & Summers, 2018). Stansbury and Summers (2018) found that after this diversion, one percentage point of increased productivity has been associated with 0.7 to 1 percent of increased median and average wage, and with only 0.4 to 0.7 percent of increased wages in production work. Wakeford (2004) finds similar results with a long-term wage-productivity elasticity of 0.58 and mentions job-shedding technology and capital intensification as plausible reasons. Strain (2019) disagrees with the work of Stansbury & Summers (2018) and argues that the reduced relationship between productivity and wages are largely dependent on the statistics used in their paper. They argue that the link is still strong when using different measures for productivity and inflation.

Real wages on labor productivity

Another stream of literature is more focused on the relationship of real wages on labor productivity, using many different statistical methods to show this. Kumar et al. (2012) use cointegration and granger causality tests and find that 1% of real wage change is related to 0.5% to 0.8% increased productivity within the Australian manufacturing sector. This effect was studied over the period 1965 to 2007 and accounts for a structural break in 1985. Narayan & Smyth (2009) find a similar result for the G7 countries in the period 1960 to 2004. Using a panel unit root and cointegration framework, they find that 1% of real wage increase is related to 0.6% of increased productivity. Strauss & Wohar

(2004) also find granger causality of real wages to productivity for 459 manufacturing industries in the US over the period 1956-1996. These discussed papers all find supporting evidence for the relationship between real wages and productivity, but all do so on a country or industry level.

Wage setting

The previously discussed real wage and productivity relationship sparks the question of how firms set their wages. Many studies have been done in the direction of productivity to real wages, proposing rent sharing as a theoretical base. Card et al. (2018) provide a recent overview of the literature regarding this direction of the relationship. And show that the found firm-level elasticity lies between 0.05 and 0.15 for many different industries and countries. Regarding inflation, Kaihatsu & Shiraki (2016) find that firms in Japan over the period 2004 to 2016 tend to reduce relative wages when short-term inflation expectations are high. They argue that this could be caused by firms being unable to pass increased cost prices on to sales prices, which seems contrary to the Economic Policy Institute (2022) finding that the majority of increased prices are going towards higher profit margins. This tendency of lowering real wages during high inflation combined with the recent increase in competition for talent, raise the question whether this could hurt firm productivity (McKinsey, 2022). This leads to the first hypothesis of this paper:

Do higher real wages cause higher firm-level productivity in the US?

Employee bargaining power

As from previous literature it is seen that no studies find an elasticity of close to one for real wages and productivity, it is unlikely that efficiency wage theory is the driver for firms to increase their wages. Outside of this efficiency wage idea, an alternative theory seems very relevant in regard to wage setting: Bargaining power. Many previous papers associate bargaining power with increased wages and highlight the importance of policy for protecting workers' wages (Kaufman, 1989 ; Folbre & Smith, 2017). Higher bargaining power is also generally associated with higher-skilled labor (Dumont & Willemé, 2012 ; Cahuc et al. 2006). Expected is then that in markets for high-skilled labor, higher wages need to be paid. This idea, combined with the idea of that firms could lose productivity due to not attracting talent, lead me to hypothesis 2:

Is the effect of real wages on productivity stronger for firms that disproportionally employ high-skilled labor?

Data

Source

The data used for this paper is Compustat data that is accessed through the WRDS platform. The data consists of US firm-level data for firms that were listed on the stock market and runs from 1950 to 2022. And includes data points per firm and year of mainly financial fundamentals like balance sheets and income statements. The selection of variables requested for this paper can be seen in table 1:

Table 1: Compustat variables

Variable	Description
Gvkey	Global company key
Year	Fiscal year
ACT	Current assets – Total
AT	Assets - Total
LCT	Current liabilities - Total
LT	Liabilities - Total
EBITDA	Earnings before interest
EMP	Employee count
REVT	Revenue – total
XLR	Staff expense – total
costat	Active/Inactive status current
Sic	Standard Industry Classic code

Average wage paid by a particular firm is calculated by dividing staff expense by employee count. This measure runs into the problem of part-time workers, but as hours worked is not available in this dataset, this is the best alternative. To calculate the real wages, the Consumer Price Index (CPI) will be added from the US bureau of labor statistics (Bureau of labor statistics, 2018). Real wages are then calculated by dividing nominal wages by the CPI and then multiplying by 100. Several firm-level control variables that are known to influence productivity are also calculated, these being: Leverage as the ratio of liabilities to assets, liquidity as the ratio of current liabilities to current assets, and the natural logarithm of total assets.

For the measurement of productivity, the total factor productivity will be estimated. Within the used dataset, several variables must be imputed to estimate the total factor productivity of a firm. This is done following a paper by P.N. Gal (2013) for the Organization for Economic Co-Operation and Development (OECD). And the imputed variables can be seen in table 2.

Table 2: Imputed variables

Variable	Imputation
Value added	Total staff cost + EBITDA
Fixed assets	Total assets – Current assets
Intermediate inputs	Total revenue – Value added

Cleaning

As there are unfortunately many measuring errors or missing values in the Compustat database, we must clean the data to get rid of extreme outliers that might influence the analysis. The cleaning process follows a paper by Li & Su (2022) and is as follows:

1. Drop firms that have a negative or missing value for the following core variables: Total staff expense, Employee count, Total current assets, Total Revenue, Total assets, Total liabilities, Current liabilities.
2. Drop firms that have a negative or missing value for the following imputed variables: Intermediate costs, Average wage, Revenue per employee, Value added.
3. Drop firms with a missing Sector Identification Code (SIC).
4. Winsorize at the 1st and 99th percentile for the following core variables: Total staff expense, Employee count, Total current assets, Total Revenue, Total assets, Total liabilities, Current liabilities.
5. Winsorize at the 1st and 99th percentile for the following imputed variables: Average wage, Leverage, Liquidity.
6. Winsorize at the 1st and 99th percentile for all measures of productivity: Revenue per employee and Total factor productivity.

Total factor productivity

As this study aims to investigate the relationship between real wages and productivity, it is important to define and measure productivity properly. A commonly used measure for this in previous literature is the output per employee or hour worked, although this measure does run into the problem of not accounting for intermediate inputs. A solution to this is to calculate productivity based on value added instead of total output, but as this measure does not account for capital intensities, this measure also falls short when comparing firms. To solve both mentioned problems, a Total Factor Productivity (TFP) should be calculated. The TFP is calculated by estimating a standard Cobb-Douglas equation for productivity like equation 1:

$$y_{it} = \alpha + \beta_l l_{it} + \beta_k k_{it} + \rho_{it} + \varepsilon_{it} \quad (1)$$

In this equation i and t indicate a firm and a particular year, respectively. y_{it} is the value added imputed like explained in table 2, l_{it} is labor input, and k_{it} is the capital stock of the firm. ρ_{it} then makes up the unobserved source of productivity we want to estimate, and ε_{it} is the idiosyncratic shock. For this paper, labor input is measured by the employee-count a firm has in a certain year. Employee count is chosen over employee expense as employee expenses are directly influenced by the regulatory environment, which can vary substantially between states within the US (U.S. Bureau of Labor Statistics, 2023). For capital stock, the fixed assets are imputed as described in table 2.

Estimating ρ_{it} using a standard OLS approach leads to bias due to several problems including a reverse causality issue that more productive firms will employ more workers. A fixed effects model can partly solve this bias but can only do so for time-invariant characteristics. Many different ways to estimate the TFP have been proposed in literature. Olley and Pakes (1992) propose a semi-parametric approach that uses investment as a proxy variable for TFP. But this method has been widely criticized over the years as it is thought that investment is not a good proxy. This criticism is also shared by Levinsohn and Petrin (2003), who propose to use intermediate costs instead of investment as a proxy. Both the Olley and Pakes (1992) as well as Levinsohn and Petrin (2003) assume that when subject to productivity shocks, firms are instantly able to change inputs at no cost. Bond & Soderbom (2005) and later Ackerberg et al. (2015) remark that the labor coefficient cannot be consistently estimated when the labor input may vary independently from the proxy variable intermediate costs, as there is a collinearity problem in the first-stage estimation. Ackerberg et al. (2015) therefore propose a (ACF) method of correcting this issue within the Levinsohn and Petrin (2003) estimator (LP). Wooldridge (2009) also proposes a method (WRDG) of circumventing the problem within the older methods of estimating TFP but does so using a one-step generalized method of moments (GMM) method. In this method he uses two equations with different sets of instruments to incorporate the relevant moment restrictions, which solves the problem within the LP (2003) estimator, as well as allow for easy estimation of robust standard errors. As the ACF corrected LP estimator and the WRDG method are deemed as the most recent and sophisticated methods of estimating TFP in the literature, both estimations will be used in this paper for robustness of results. The methods will be performed using the stata command -prodest-, and as both methods require the intermediate inputs used by a firm in a particular year, this variable will be imputed as described in table 2. For a more in-dept and technical description of the discussed methods of estimating TFP, as well as of the stata command -prodest-, I refer to Rovigatti & Mollisi (2018).

Firm Heterogeneity

As in the literature it is found that higher bargaining power of employees is generally related to industries that employ high-skilled workers. In this study the distinction will be made between Knowledge- and Technology-Intensive (KTI) industries and non-KTI industries as described by the US National Science Board (NSB) (Okrent, 2022).

The NSB (2022) makes this distinction for firms based on an earlier paper by Galindo-Rueda & Verger (2016), who cluster industries into 5 levels of research and development (R&D) intensity. This R&D intensity is calculated by the ratio of each industry's business R&D expense and that industry's value-added output. Only the top 2 clusters (high and medium-high) are classified as KTI industries by the NSB. It is seen that KTI industries employ disproportionately more workers in science, technology, engineering, and mathematics (STEM) occupations. Which are generally more high-skilled (Noonan, 2017). The NSB (2022) makes a distinction of 11 industries that they regard as KTI industries, which are linked to their respective SIC codes present in the Compustat dataset. The relevant combinations of KTI industries and SIC codes can be seen in table 3.

Table 3: KTI industries as per the AEA and their respective SIC codes.

KTI industries	SIC code
Chemicals	28xx
Pharma	2833 ; 2834
Computer, electronic, and optical products	3570 – 3599 ; 36xx ; 3827
Electrical equipment	36xx
Machinery and equipment	35xx
Motor vehicles, trailers, and semi-trailers	37xx
Air and spacecraft and related machinery	37xx
Medical and dental instruments	38xx
IT and other information services	7370 - 7374
Software publishing	7370 - 7374
Scientific research and development	783x

Summary statistics

In table 4 the summary statistics for the retrieved data after the cleaning process can be seen. The resulting unbalanced panel dataset consists of 3,464 US-based firms spanning 390 SIC-code industries. The firms are in the dataset for 11,4 years (SD 9.5) on average, which results in 34,707 observations in total from the year 1950 to 2022. The year with the lowest number of observations is the year 1950 with 117 observations. The sample is biased towards large companies, as the average employee count is 13,835. This is expected as the Compustat database consists of only publicly listed firms.

A variance inflation factor (VIF) is performed to test for multicollinearity within the explanatory variables. This test can be seen in appendix 1 and shows there is no problems in this regard. Additionally, I assess whether both ways of estimating productivity seem to measure the same level of productivity. For this I show in appendix 2 that the Ackerberg et al. (2015) (ACF) and the Wooldridge (2009) (WRDG) measures of TFP show a high correlation of 0.7635. From this I conclude that both techniques measure the same metric and can therefore be used as sensitivity tests for each other.

Table 4: Summary statistics for the full sample

X 1,000,000	N	Mean	SD	Min	Max
Total current assets	34,707	627.7	1,281	0.250	15,524
Total assets	34,707	2,315	4,583	0.599	83,098
Ebitda	34,707	313.6	657.5	-1,462	9,637
Current liabilities	34,707	486.0	1,011	0.490	6,776
Total liabilities	34,707	1,364	2,744	0.500	21,837
Total revenue	34,707	1,645	3,134	0.350	27,066
Total employee costs	34,707	371.3	720.9	0.126	9,365
Total net assets	34,707	1,687	3,614	0.00500	79,907
Value added	34,707	684.9	1,257	0.120	14,551
Intermediate costs	34,707	960.0	2,058	0.00300	23,229
Real values					
Employee count	34,707	13,835	22,552	5	156,000
Real average wage	34,707	25,895	12,769	1,029	267,640
Revenue per employee	34,707	155,085	176,688	10,178	1.339e+06
Leverage	34,707	0.542	0.194	0.117	1.422
Liquidity	34,707	1.735	1.035	0.289	5.963
TFP (WRDG)	34,707	0.856	0.536	0.102	2.875
TFP (ACF)	34,707	0.204	0.123	0.0190	1.916
Number of firms	3,464	3,464	3,464	3,464	3,464

Model specification

To answer the research questions of this paper, a dynamic panel model will be used. Classic Pooled OLS or Fixed effects models are prone to reverse causality due to the relationship from productivity to real wages described in the literature review. These models will therefore give biased estimates and are not suitable for the analysis. Dynamic panel models are used to determine the relationship between a dependent and independent variable by adding lagged values of the dependent variable to the right-hand side of the equation. And are common within literature when evaluating panel data samples with a large number of observed units N over a relatively short timeframe T. This results in the following equation:

$$Y_{it} = \alpha + \gamma_1 Y_{it-1} + \gamma_2 Y_{it-2} + \beta_1 X_{it} + C_{it} + T_t + \mu_i + \varepsilon_{it} \qquad (2)$$

The dependent variable for this model is productivity Y_{it} for firm i in year t. The main coefficient of interest of this model is β_1, as this measures the effect of real wage on productivity. C_{it} refers to the control variables added to the model that were available in the Compustat data and are known to affect productivity from earlier research (İmrohoroğlu & Tüzel, 2014), these are leverage, liquidity, and total assets as logs for a firm i in time t. The model also includes firm fixed effects μ_i to account for unobserved time-invariant firm characteristics. As well as time dummies T_t to account for any trends that could influence the results. ε_{it} refers to the idiosyncratic shock for firm i in year t. A fixed- or random effects model is used to estimate equation (2), based on the result of a Hausman test that can be seen in appendix 3 and 4.

Basic estimations like a fixed- or random effects model do run into problems as described by Nickell (1981). He shows that adding lagged dependent variables creates a correlation of the idiosyncratic shock with these lagged dependent variables, which in turn provides biased estimates. This so-called Nickell bias is particularly present in samples with a short time period T but can still be relevant for samples with larger timeframes (T>10). As the used sample for this study is an unbalanced panel with a timeframe of on average 11.4, it can be expected that the Nickell bias is relevant for this study. Therefore, a more sophisticated methodology will also be presented.

A common way of dealing with the Nickell bias is made popular by Arellano & Bond (1991). In this difference generalized method of moments (GMM), the first differences of equation 2 are taken to remove time-invariant unobserved heterogeneity, after which further lags of the differenced dependent variable are taken as instruments for the dependent variable. This method is shown to be able to account for the Nickell bias, as well as reverse causality and unobserved heterogeneity (Leszczensky & Wolbring, 2022). As this difference GMM model will be used as a sensitivity test for the more standard fixed effects model, only the lags of the dependent variable will be entered as endogenous. All other variables are entered as exogenous.

In a later paper by Blundell & Bond (1998), they highlight a potential issue with weak instruments in the difference GMM and propose a system GMM to resolve this issue. But as this system GMM requires the assumption that all exogenous variables are uncorrelated with the fixed effects, it is not valid for this analysis. Therefore, only the difference GMM is estimated for this paper.

Caution is advised as several restrictions must be met for the estimates to be valid in a difference GMM. To evaluate whether this model gives valid estimates for the sample used in this paper, several tests are performed. To assess the validity of the instruments used in the model, a Hansen J test for over-identification will be reported in the results (Hansen, 1982). Anderson & Sørenson (1996) identify that the Hansen J test provides unrealistically high p-values and false positives too often when using a large number of instruments, which is especially relevant in panels where T is relatively large like the one in this study. Therefore, the number of instruments in the model will be greatly reduced by “collapsing” the instruments. In this procedure an instrument for the dependent variable is made for every variable and lag distance, contrary to the default, where an instrument is made for every variable, lag distance, and time period (Roodman, 2009). A second condition for GMM models is that serial autocorrelation on first differences is expected, but serial correlation of higher order differences is not allowed. I report the Arellano & Bond (AR) test for the first and second differences, to evaluate whether these specifications hold (Arellano & Bond, 1991). Additionally, the Windmeijer (2005) correction is applied to retrieve robust standard errors, and the first differencing is replaced subtracting the mean of all future available observations of a variable. This last transformation is called using ‘orthogonal deviations’ and is recommended by Arellano & Bover (1995) for unbalanced datasets like the one used in this paper as the differencing can calculated for every value regardless of gaps in panels. For the difference GMM method, the model is estimated as a basic POLS and Fixed effects model too, as Bond (2002) mentions these two estimators of the lagged dependent variable can function as range for good estimators of the true parameters. As he concludes that the POLS and Fixed effects dynamic panel models are upwards- and downwards biased, respectively. The difference GMM model will be estimated using the -xtabond2- stata command created by Roodman (2009), for more information on the technicalities of this command I refer to his introductory paper.

Results

From a significant Hausman test for both measures of TFP it is concluded that a fixed effects model is best suited for the analysis of this paper. Table 5 shows the results of the dynamic fixed model evaluated for both the ACF and WRDG method of estimating TFP. As all variables in the model are entered as natural logarithms, the coefficients can be interpreted as elasticities. Because of the lags of the dependent variable in the models, the average T for the full sample is 14.27 (SD 9.12) and 13.88 (SD 9.47) and 14.37 (SD 9.02) for KTI and non-KTI samples, respectively. In model (1) and (4), an elasticity from of 0.401% and 0.316% is seen for the ACF and WRDG measures of productivity, respectively. These coefficients are highly statistically significant. These results show evidence for hypothesis 1. In models (2) and (3), as well as models (5) and (6), a comparison is made between KTI and non-KTI firms. In both sets of models, it is shown that the elasticity of average real wage on productivity is higher for KTI firms than for non-KTI firms. The coefficients for these models are again highly significant, which provides evidence for hypothesis two. But as there is potential for Nickell (1981) bias in both models, hard conclusions are to be made conservatively.

Table 5: Dynamic fixed effects model of real average wage on TFP

	(1) ACF	(2) ACF	(3) ACF	(4) WRDG	(5) WRDG	(6) WRDG
Sample	Full	KTI	Non-KTI	Full	KTI	Non-KTI
L1 Productivity	0.452***	0.436***	0.450***	0.493***	0.481***	0.488***
	(0.0176)	(0.0388)	(0.0197)	(0.0187)	(0.0415)	(0.0208)
L2 Productivity	0.0328**	0.00884	0.0331**	0.0466***	0.0112	0.0500***
	(0.0136)	(0.0308)	(0.0152)	(0.0146)	(0.0344)	(0.0159)
Real average wage	0.401***	0.459***	0.392***	0.316***	0.373***	0.308***
	(0.0153)	(0.0346)	(0.0165)	(0.0147)	(0.0342)	(0.0156)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	26,369	5,389	20,980	26,369	5,389	20,980
R-squared	0.732	0.612	0.759	0.813	0.746	0.830
Number of firms	2,448	593	1,855	2,448	593	1,855

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: All variables in the model are entered as logs. 'ACF' and 'WRDG' refer to the different methods of TFP estimation as explained earlier. KTI and non-KTI samples refer to the different SIC codes explained in the methodology section.

Table 6: Difference GMM model of real average wage on TFP

	(7) ACF	(8) WRDG	(9) ACF	(10) WRDG	(11) ACF	(12) WRDG
Model	Pooled OLS	Pooled OLS	Fixed effects	Fixed effects	Diff GMM	Diff GMM
L1 Productivity	0.700***	0.740***	0.452***	0.493***	0.569***	0.615***
	(0.0149)	(0.0158)	(0.0176)	(0.0187)	(0.0339)	(0.0260)
L2 Productivity	0.131***	0.153***	0.0328**	0.0466***	0.0331*	0.0435**
	(0.0140)	(0.0151)	(0.0136)	(0.0146)	(0.0177)	(0.0174)
Real average wage	0.105***	0.0565***	0.401***	0.316***	0.364***	0.282***
	(0.00421)	(0.00339)	(0.0153)	(0.0147)	(0.0194)	(0.0159)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes
Instruments					184	184
Hansen J-test					0.199	0.083
AR(1)					0.000	0.000
AR(2)					0.606	0.428
Observations	26,369	26,369	26,369	26,369	23,921	23,921
Number of firms			2,448	2,448	2,138	2,138

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Note: All variables in the model are entered as logs. As described in the methodology section, the lags of the dependent variable are entered as endogenous in the difference GMM model. To compare the results with the dynamic fixed effects model, all other variables are entered as exogenous. 'ACF' and 'WRDG' refer to the different methods of TFP estimation as explained earlier.

Table 6 shows the results of several dynamic panel models for the effect of real average wage on both estimations of TFP, including a difference GMM model to evaluate sensitivity to the Nickell bias. Models (7) and (8) show a pooled OLS (POLS) estimation and as explained in the model estimation section, function as an upper boundary of a reasonable coefficient of the first lag of productivity, which are 0.700 and 0.740 respectively. Models (9) and (10) show a fixed effects estimation and function as the lower boundary of a reasonable coefficient of the first lag of productivity. These are found to be 0.452 and 0.493, respectively. In models (11) and (12), a difference GMM model is estimated for the same equation. Regarding the upper and lower boundaries of the coefficient of the first lag of productivity, it is seen that for both models the coefficient lies within the determined boundaries of reasonable coefficients, which gives an indication that the model is performing as expected. The results of the Hansen J-test of 0.199 and 0.083 respectively both fail to reject the null hypothesis of instrument validity, and do not give hints of unrealistically high p-values. The AR(1) test results show a 0.000 significance for both models (11) and (12), showing the expected serial correlation in the first differences. And the AR(2) results of 0.606 and 0.428 respectively show that the condition of no serial correlation in the second order differences is also met. To sum up, these diagnostics provide support for the correct specification of the model. In terms of results, in models

(11) and (12) it is seen that the coefficient for average real wage is still highly significant, albeit lower than for the fixed effects model. Indicating that there is Nickell bias present in the fixed effects model. The coefficients indicate a 0.364% and 0.282% elasticity of real average wage on productivity respectively, supporting hypothesis one.

Table 7 shows the results of the firm heterogeneity analysis in a difference GMM method. Due to the reduced sample of KTI firms, a restriction is made on the instruments of the dependent variable used in the model to combat the weakness problem of the Hansen J test warned for by Anderson & Sørenson (1996). For comparability of the models, the same restriction of 14 lags of depth is used for both the KTI and Non-KTI models. For the ACF estimator of TFP, it is seen that model (14) does not show the expected serial correlation in the first differences as the p-value for the AR(1) test is a non-significant 0.109. Model (14) is therefore not correctly specified, and no comparison can be made between models (13) and (14). Models (15) and (16) show the same difference GMM model but for the TFP estimator WRDG. The Hansen J-test show a p-value of 0.233 and 0.296 respectively and therefore fail to reject the validity of the instruments. Again, no hints of unrealistically high p-values due to high instrument count are found. AR(1)-test values of 0.011 and 0.004 respectively combined with AR(2)-test values of 0.510 and 0.575 confirm both models also satisfy the condition of no serial correlation of higher order differences. Again, the diagnostics provide an indication that the model is correctly specified. The highly significant coefficients for real average wage of 0.355 and 0.286 respectively again show that the effect of real average wage on productivity is found to be higher within KTI firms compared to their non-KTI counterparts, providing more evidence for hypothesis 2.

Table 7: Difference GMM model for average real wage on productivity for subsamples KTI and Non-KTI

	(13) ACF	(14) ACF	(15) WRDG	(16) WRDG
Sample	KTI	Non-KTI	KTI	Non-KTI
L1 Productivity	0.477***	0.272*	0.639***	0.546***
	(0.174)	(0.165)	(0.210)	(0.151)
L2 Productivity	-0.0149	0.204*	-0.0617	0.0679
	(0.119)	(0.113)	(0.121)	(0.105)
Real average wage	0.455***	0.406***	0.355***	0.286***
	(0.0388)	(0.0335)	(0.0378)	(0.0258)
Controls	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes
Instruments	99	99	99	99
Hansen J-test	0.433	0.115	0.233	0.296
AR(1)	0.017	0.109	0.011	0.004
AR(2)	0.751	0.067	0.510	0.575
Observations	4,796	19,125	4,796	19,125
Number of firms	506	1,632	506	1,632

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: All variables in the model are entered as logs. As described in the methodology section, the lags of the dependent variable are entered as endogenous in the difference GMM model. To compare the results with the dynamic fixed effects model, all other variables are entered as exogenous. 'ACF' and 'WRDG' refer to the different methods of TFP estimation as explained earlier. KTI and non-KTI samples refer to the different SIC codes explained in the methodology section.

Robustness checks

Too many instruments

As Roodman (2009) writes in his paper, a large danger to GMM type models is that of too many instruments. He describes this results in weak instruments as well as biased Hansen J-tests. Windmeijer (2005) also finds using monte-carlo simulations that reducing instrument counts can greatly reduce bias in the coefficient of interest. To test for this bias, I present a replication of models 11 and 12 with a large reduction of instruments from 184 to 100. The results are shown in table 8. We see that models 17 and 18 both fail to reject the Hansen J-test for invalid instruments with P-values of 0.278 and 0.276, respectively. And that the AR(1) and AR(2) tests also show no evidence of serial correlation in higher differences with p-values of 0.000 in the AR(1) test and 0.710 and 0.461 in the AR(2) test respectively. Additionally, the coefficients for L1 productivity are also very similar to the higher instrument count versions and fall within the upper and lower boundaries provided by the POLS and fixed effects models in table 6. These diagnostics again suggest that both models are specified correctly. For the coefficient of interest, we see that the coefficients for Real average wage are also extremely similar to the values in models 11 and 12, with a value of 0.364 for model 17 and 0.283 for model 18. These low differences suggest that there is no issue of too many instruments bias in the earlier models.

Table 8: Replication of models 11 and 12 with greatly reduced instrument count.

	(17) ACF	(18) WRDG
L1 Productivity	0.547***	0.613***
	(0.0349)	(0.0264)
L2 Productivity	0.0256	0.0415**
	(0.0181)	(0.0175)
Real average wage	0.364***	0.283***
	(0.0196)	(0.0160)
Controls	Yes	Yes
Year dummies	Yes	Yes
Instruments	100	100
Hansen J-test	0.278	0.276
AR(1)	0.000	0.000
AR(2)	0.710	0.461
Observations	23,921	23,921
Number of firm	2,138	2,138

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: All variables in the model are entered as logs. As described in the methodology section, the lags of the dependent variable are entered as endogenous in the difference GMM model. To compare the results with the dynamic fixed effects model, all other variables are entered as exogenous. 'ACF' and 'WRDG' refer to the different methods of TFP estimation as explained earlier.

1980 – 2022 sample

One limitation of using the entire Compustat database is that the effects measured over the entire 1950 – 2022 sample could be influenced by the earlier years and therefore might not be as relevant for the current situation. Especially due to the evidence of a structural break that comes up in the literature surrounding the wage productivity gap Kumar et al. (2012). Additionally, the early years in the database have substantially less observations than the later years, which could also make the estimations less reliable. Therefore, as an extra robustness check, I present the same analysis for a subsample that starts in 1980. Table 9 shows this additional analysis. Models 19 and 20 both fail to reject the Hansen J-test for invalid instruments with P-values of 0.257 and 0.389, respectively. The AR(1) and AR(2) tests also show no evidence of serial correlation in higher differences with p-values of 0.000 for the AR(1) test and 0.577 and 0.954 for the AR(2) test respectively. The upper and lower boundaries for the coefficient for L1 productivity in this sample, estimated by a Pooled OLS and Fixed effects model for both estimates of TFP, can be found in appendix table 5. And show that the coefficients of L1 productivity fall comfortably within these boundaries. To summarize, the diagnostics used to assess the model again suggest that the model is correctly specified. For the variable of interest real average wage, there is no change in the direction of the effect, but we see a slight increase in the coefficients. For the ACF estimator of TFP, the coefficient rose from 0.364 in model 11 to 0.413 in model 19. And for the WRDG estimator of TFP, the coefficient rose from 0.286 in model 12 to 0.314 in model 20. These coefficients are all highly statistically significant and show that the effect of real wage on productivity is stronger in the timeframe 1980 – 2022 than in the entire sample starting in 1950.

Table 9: Replication of models 11 and 12 for the sample 1980 – 2022.

	(19)	(20)
VARIABLES	ACF	WRDG
L1 Productivity	0.465***	0.526***
	(0.0443)	(0.0324)
L2 Productivity	0.0158	0.0323
	(0.0202)	(0.0200)
Real average wage	0.413***	0.314***
	(0.0232)	(0.0192)
Controls	Yes	Yes
Year dummies	Yes	Yes
Instruments	156	156
Hansen J-test	0.257	0.389
AR(1)	0.000	0.000
AR(2)	0.577	0.954
Observations	14,262	14,262
Number of firm	1,728	1,728

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: All variables in the model are entered as logs. As described in the methodology section, the lags of the dependent variable are entered as endogenous in the difference GMM model. To compare the results with the dynamic fixed effects model, all other variables are entered as exogenous. 'ACF' and 'WRDG' refer to the different methods of TFP estimation as explained earlier.

Discussion, Conclusions, and limitations.

Discussion and conclusions

Within the literature discussed in this paper an elasticity of 0.4 to 0.8 is found for the relationship between real wages and productivity with long run methodologies like cointegration and granger causality. But attempts to study a more classic causal relationship show contrary results on the firm-level, with found results for the elasticity of productivity to real wages between 0.05 and 0.15. Indicating that there are strong rigidities present that separate the long-run estimations from the short-run counterparts.

This study joins the second, more causal strain of papers, but for the direction of real wages to productivity. And finds an elasticity of 0.364 or 0.282 for the full sample, depending on the estimation technique of Total Factor Productivity. Using a difference GMM method that is robust to the too many instruments problem. For the studied 1980 – 2022 sample, these elasticities are found to be slightly higher, at 0.413 and 0.314. Which is likely due to the changed mix of firms within the two samples.

These results are significantly lower than the country or industry level long run results presented in the literature review, suggesting that there are also rigidities present in this direction of the relationship. A possible rigidity could be that higher real wages do not instantly result in higher productivity. As it could be assumed that new talent attracted by higher wages need time to arrive to their maximum potential, which assumption is strengthened by a survey study by the Training Industry Quarterly (2012). Where it is found that 75% of respondents say that it takes two years for new employees to be optimally productive within their teams, and that employee performance usually peaks at around 5 to 10 years. Further research could be done to uncover this potentially lagged effect of real wage on productivity.

This lagged effect of real wage on productivity could result in short term bias in hiring, as it seems that on the short term lower real wages have less of an effect on productivity than on the long term. Hardcopf et al. (2017) show that managers can show bias towards cost cutting tactics that could be in misalignment with the firms' long-term strategy. And this could mean that they would keep real wages lower than optimal on a short-run scope. This potential short-term bias of firms would also have implications for policy makers that are trying to protect workers from high inflation. As if firms have a weak incentive to match wages to inflation, governments might have to step in to protect buying power in the short term.

For the hypothesized difference that bargaining power makes on the effect of real wage on productivity, it is found that the coefficient for real average wage is higher for KTI industries compared to their non-KTI counterparts in all models. This suggests that bargaining power does make the relationship of real wage to productivity stronger and is in line with the evidence that in labor markets with a higher worker bargaining power, higher wages need to be paid for productive employees (Kaufman, 1989 ; Folbre & Smith, 2017). For firms within KTI industries this implies that their productivity is more short-run sensitive to real wages. And that on a short timeframe, there is more to gain and to lose within their wage setting strategy compared to their non-KTI counterparts. Regarding policy makers and unions, this result implies that bargaining power is a relevant factor for short term retainment of purchasing power, as higher bargaining power forces firms to match their wages closer to the inflation to be productive. And stresses the need for strong laws and unions to protect bargaining power especially in non-KTI industries.

Limitations

There are several limitations to this study that will be discussed in this section.

First, the database used for this study creates several restrictions regarding the validity of the research. The sample used for this paper is very biased towards large, publicly listed firms and should therefore only be interpreted accordingly. The database also leaves out some important details that are relevant to the studied relationship. Examples of this are that the labor costs are not corrected for hours worked and quality of work, and that these factors are not taken into account within the TFP estimators. Additionally, some variables used in this analysis had to be imputed from other variables, which according to the paper by P.N. Gal (2013) does not create large problems but could reduce accuracy somewhat. More accurate studies could be done by using more detailed data, but as far as previous literature goes, no such datasets are currently available to study the long-term relationship as presented in this paper.

Second, the bargaining power analysis could have been more firm-level specific. As this study researches the bargaining power hypothesis by making subsamples of industries, some of the firm-level heterogeneity that could have been exploited in this dataset are lost. Examples of this could have been to make distinctions based on R&D spending or the ratio of blue to white collar workers. But such data unfortunately was not available in sufficient quality within this dataset.

Third, in terms of model specification, it is hard to assume that the presented coefficients contain no bias. As often in models, exogeneity of regressors is hard to satisfy, and the relatively small number of control variables available in the dataset do not help this case. Again, further research could be done on more detailed datasets that allow for more correction of potential biases and therefore reach a more precise result. A suggestion given by Leszczensky & Wolbring (2022) regarding endogeneity and reverse causality in panel models is to use a structural equation modeling / maximum likelihood

(SEM/ML) technique to account for these issues. As this method generally needs a balanced panel it was not suited for this particular research, but combined with the earlier recommendations regarding the optimal sample for this research question, provides a suggestion for future research.

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Appendix

Appendix 1: VIF test

VARIABLES	VIF	1/VIF
Real average wage (log)	1.65	0.604407
Total assets (log)	1.30	0.769266
Leverage	1.62	0.619161
Liquidity	1.88	0.533234

Appendix 2: correlation of TFP measures

Correlation table	WRDG
ACF	0.7635

Appendix 3: Hausman test for random- and fixed effects models of equation 1 with TFP estimated by WRDG method.

Hausman test		Ho: Difference in coefficients not systematic
Chi2(76)	= 2215.82	
Prob > Chi2	= 0.0000	

Appendix 4: Hausman test for random- and fixed effects models of equation 1 with TFP estimated by ACF method.

Hausman test		Ho: Difference in coefficients not systematic
Chi2(76)	= 2183.40	
Prob > Chi2	= 0.0000	

Appendix 5: Pooled OLS and Fixed effects benchmarks for the 1980 – 2022 subsample.

	(21)	(22)	(23)	(24)
	ACF	WRDG	ACF	WRDG
Model	Pooled OLS	Pooled OLS	Fixed effects	Fixed effects
L1 Productivity	0.651***	0.703***	0.378***	0.425***
	(0.0169)	(0.0182)	(0.0208)	(0.0223)
L2 Productivity	0.117***	0.152***	0.0209	0.0398**
	(0.0156)	(0.0172)	(0.0157)	(0.0170)
Real average wage	0.138***	0.0703***	0.436***	0.338***
Controls	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes
Observations	16,284	16,284	16,284	16,284
R-squared	0.812	0.880	0.496	0.528
Number of firms			2,022	2,022

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Note: All variables in the model are entered as logs. 'ACF' and 'WRDG' refer to the different methods of TFP estimation as explained earlier.