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Does wage rigidity make firms riskier? Evidence from long-horizon return predictability☆

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Abstract

The relationship between sticky wages and risk has important asset pricing implications. Like operating leverage, sticky wages are a source of risk for the firm. Firms, industries, regions, or times with especially high or rigid wages are especially risky. If wages are sticky, then wage growth should negatively forecast future stock returns because falling wages are associated with even bigger falls in output, and increases in operating leverage. Indeed, this is the case in aggregate, industry, and U.S. state level data. Furthermore, this relation is stronger in industries and U.S. states with higher wage rigidity.

JEL classification: E2, G1, J3

Keywords: keywords here, in the form: keyword, keyword Wage rigidity, Return predictability, Operating leverage code, code

1. Introduction

Wage rigidity is an important determinant of firms' risk and cost of capital. Sticky wages (wages that are imperfectly correlated with the marginal product of labor) create an additional source of risk for the firm. This implies that firms, industries, regions, or time periods with especially high or rigid wages are therefore especially risky. In particular if wages are sticky, then wage growth should negatively forecast future stock

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returns because falling wages are associated with even bigger falls in output, and with increases in operating leverage. This paper indeed finds this to be the case in aggregate, industry, and U.S. state level data. Furthermore, this paper finds that industries and U.S. states with higher wage rigidity have a stronger relationship between wages and returns.

Sticky wages are an important and widely studied feature of labor markets (Calvo (1982), Taylor (1983), Taylor (1999), Shimer (2005), Hall (2006), Gertler and Trigari (2009)), however their asset pricing implications have received less attention. Danthine and Donaldson (2002) and more recently Favilukis and Lin (2015) have shown that they can improve the asset pricing implications of a production economy, while Gourio (2007) shows that they may help explain cross-sectional differences in returns as well. This paper shows that in the presence of sticky wages, wage growth becomes a state variable and negatively forecasts future returns. This forecastability is stronger in times periods, industries, or regions where wages are more rigid, or where the labor share is high.

This paper starts with a simple model to illustrate the intuition of the key mechanism. The key feature of this model is that wages are not equal to the marginal product of labor, as in standard models. Rather, as in Shimer (2010), wages follow an autoregressive process where the innovation is related to the marginal product of labor. Therefore, wages are backward looking. In bad (good) times, output falls (rises) but wages do not fall (rise) by as much as output, which makes equity riskier because of relatively higher wage obligations by the firm. This model shows that wage growth negatively forecasts future stock returns if wage rigidity is present, with stronger forecastability if rigidity is stronger and no forecastability if the wage is equal to the marginal product of labor. The simple model also implies that wage growth and labor share are negatively correlated and that labor share positively forecasts stock returns due to the operating leverage effect.

The model is also extended to allow labor markets to affect returns through operating leverage as in the simple model, but also through changing the dividend's share in the pricing kernel - a channel emphasized by Santos and Veronesi (2006). Santos and Veronesi (2006) show that as labor share becomes a larger part of aggregate output, dividends become a smaller part and are therefore less correlated with aggregate output and less risky; this leads to lower expected stock returns. The extended model shows that i) the effect of labor share on stock returns may be ambiguous depending upon model specification, and ii) more importantly, the prediction that wage growth negatively forecasts future stock returns is robust when wage rigidity is present. This finding motivates us to focus on wage growth channel in our empirical tests. The results in the data are consistent with the model.

Then the implications of this model are tested. There are three main results. Our first result concerns aggregate data; long horizon returns are regressed on wage growth. This result shows that aggregate wage growth negatively forecasts aggregate excess return. This result appears robust to sub-sample analysis, and to the inclusion of standard predictors such as the price-to-earnings ratio or the consumption-to-wealth ratio (CAY), which do not weaken this relationship.

The next two results are at the disaggregate level (independently either for industries or for U.S. states), where a two stage approach is employed. In the first stage long horizon industry (or state) returns are regressed on wage growth. This result shows that most of the coefficients are negative; this is consistent with our first hypothesis on aggregate coefficients being negative. The second stage regressions show that industries (or states) with the most wage rigidity also have the most negative coefficients from the first stage. We proxy for wage rigidity by measuring the autocorrelation of wage growth, the inverse of the volatility of wage growth, and the share of votes that was Democratic (available for states only).

Related literature In addition to the macroeconomic literature on wage rigidity, our work relates to two separate strands of financial research, the first on (mostly aggregate) return predictability and the second on the interaction of labor markets and financial returns. It has been shown in the past that aggregate stock returns are forecastable by variables which proxy either for aggregate risk, aggregate risk aversion, or sentiment. For example the price-to-earnings ratio (Campbell and Shiller (1988)) or the consumption-to-wealth ratio (Lettau and Ludvigson (2001)).[1] Santos and Veronesi (2006) show that even without movements in aggregate risk, risk aversion, or sentiment the labor income to consumption ratio should also forecast stock returns due to changing importance of equity in the investors' total portfolio. This paper studies changes in operating (labor) leverage due to changes in wage growth, which also leads to aggregate return predictability but is unrelated to the channels described above. In addition, wage growth forecasts return in the cross-section. Interestingly, unlike much of the previous literature (i.e. Campbell and Shiller (1988) and Lettau and Ludvigson (2001)) but like Santos and Veronesi (2006), the forecasting variable in this paper is not a scaled stock price or other financial variable, but rather a pure macroeconomic variable.

There has been less work done on tying labor frictions to risk and asset returns. The two papers closest to ours are Gourio (2007) and Tuzel and Zhang (2015). Gourio (2007) explores the empirical implications of smooth wages for the cross-section of U.S. publicly traded firms. He finds that profits are most volatile for low market-to-book (value) firms because they have a smaller gap between output and wages. These firms are therefore more risky.[2] This paper differs in that Gourio (2007) focuses on the value premium and on average returns, while this paper studies risk in aggregate, industry,

[1]Other notable forecasting variables include the dividend yield (Campbell and Shiller (1988), Fama and French (1988), and Hodrick (1992)), the relative Treasury bill rate, defined as the Treasury bill rate minus its past four-quarter moving average (Fama and Schwert (1973) and Fama (1981)), the term and default premiums (Keim and Stambaugh (1986) and Fama and French (1989)), the aggregate investment-to-capital ratio (Cochrane (1991)), and new orders (Jones and Tuzel (2013)).

[2]Similarly, Carlson et al. (2004) and Novy-Marx (2011) argue that differences in operating leverage across are responsible for the value premium. However, neither paper discusses wages.

and regional portfolios through long run return predictability by wage growth. Tuzel and Zhang (2015) look at the reverse problem by identifying regions where wages co-move a lot with aggregate shocks - presumably these are regions with less wage rigidity. They show that average returns in these industries are relatively low. Stickiness need not only work through wages, Weber (2015) shows that firms with sticky prices earn higher average returns.

Other related work includes Belo et al. (2014), who show that firms with low hiring rates have significantly higher average equity returns. Rosett (2001) and Chen et al. (2011) both show that unionized industries have a higher cost of equity, while Schmalz (2012) shows that firms tend to decrease leverage after unionization. Unlike these studies, this paper relates labor market frictions to time-variations in risk and in expected return through long-horizon return predictability. Note that the approach in the paper would not be possible with union data because cross-sectional union data is only available starting in 1984, which gives too short of a time series to detect time-varying risk. However, since wage rigidity can arise even without unions, and since unions make up a fairly small fraction of the U.S. work force,[3] we view our findings as a complimentary and more general confirmation for the importance of labor market frictions.

The rest of our paper is laid out as follows. Section 2 presents a simple model to get intuition for the empirical findings. Section 3 describe the data and the boot strap inference approach used in the paper. Section 4 presents the empirical results. Section 5 concludes.

2. Model and Empirical Specification

This section solves two models to motivate the empirical exercise. The first model shows that wage rigidity can lead to long horizon return predictability, with low wage

[3]According to the Bureau of Labor Statistics 12% of the U.S. work force was unionized as of 2011.

growth leading to high future expected returns. The second model is an extension of the first and shows that the effect of labor share on long horizon returns is ambiguous, even if wages negatively forecast future expected returns.

2.1. Simple model

Empirically, wages are significantly smoother than output and imperfectly correlated with output. From the firm owner's perspective, relative rigidity of the firm's wage bill looks like leverage, making equity especially risky because during bad times wages do not fall by as much as output does. Because output falls by more than wages, falling wages are associated with rising operating leverage, higher risk, and higher expected equity returns. Note that absent labor market frictions, the wage will equal to the marginal product of labor and will be nearly perfectly correlated with output; as a result there will be no relationship between wage growth and expected asset returns.

This section will solve a very simple model[4] which can formalize the above intuition and guide our empirical exercise. The model's results are consistent with Favilukis and Lin (2015), who explore the asset pricing implications of wage rigidity in a calibrated, general equilibrium, production economy and show that sticky wages induce time-varying expected equity returns.

In our simple model, output is produced from labor N_t and labor-augmenting productivity A_t: $Y_t = A_t N_t^{\alpha}$. Aggregate labor supply is inelastic so that $N_t = 1$. There is no capital so that all aggregate output is consumed: $C_t = A_t N_t^{\alpha}$. Financial markets are complete and there is a representative household who maximizes a CRRA utility function, which implies that the stochastic discount factor which prices all assets in the

[4]Of course, one can think of more complicated models where wage growth will forecast risk even without rigidity. For example, in a habit model the start of a recession is associated with low wage growth, higher risk aversion, and higher expected returns. We believe that our cross-sectional results rule out many such explanations, although we cannot rule out all alternative explanations. Furthermore, in the case of a habit model, all predictability should come from movements in the price-to-earnings (or price-to-dividend) ratio. In the empirical section we show that wage growth forecasts stock returns even after including the price-to-earnings ratio.

economy is $M_{t+1} = \beta \left(\frac{C_{t+1}}{C_t}\right)^{-\gamma} = \beta \left(\frac{A_{t+1}}{A_t}\right)^{-\gamma}$.

An individual firm's dividend is equal to its output minus its wage bill $D_t = A_t N_t^{\alpha} - W_t N_t$; since all firm's are identical and $N_t = 1$ in equilibrium, a representative firm's dividend is $D_t = A_t - W_t$. The firm's value is the discounted present value of dividends: $V_t = D_t + E_t[M_{t+1} V_{t+1}]$.

Sticky wage is assumed as the following:

$$W_t = \mu W_{t-1} + (1 - \mu) W_t^* \tag{1}$$

where μ is the degree of stickiness and W_t^* is the target wage. This wage bill is similar in spirit to Shimer (2010) and Gertler and Trigari (2009), the average wage is an average of the last period's average wage W_{t-1} and the target wage.[5] We assume that the target wage is proportional to labor-augmenting productivity: $W_t^* = \alpha A_t$. Note that without labor market frictions ($\mu = 0$), the equilibrium average wage is equal to the marginal product of labor, which is exactly equal to the target wage as defined above. The parameter α is related to labor share: when there is no wage rigidity it is exactly equal to labor share, otherwise it is the average labor share. Productivity growth is assumed to be i.i.d.: $\frac{A_{t+1}}{A_t} = 1 + \sigma^A \epsilon_{t+1}^A$.

The appendix shows that there is an analytic solution for firm value:

$$V_t = V_A A_t + V_W W_{t-1} \tag{2}$$

where $V_A > 0$ and $V_W < 0$ are constants. If there is no rigidity ($\mu = 0$), then the firm value does not depend on W_{t-1} ($V_W = 0$).

The model above is simulated for the parameters listed in Table 5. Time preference is

[5] In Favilukis and Lin (2015), infrequent renegotiation of wages leads to a similar process for the aggregate wage.

$\beta = 0.95$ and risk aversion is set in accordance with standard values, $\gamma = 5$. Conditional volatility of productivity growth $\sigma^A = 0.04$ is set to roughly match output growth volatility. $\mu = 0.75$ implies average wage duration of four years, it also implies that the autocorrelation of labor share is 0.75 (compared to 0.86 in the data). Note that productivity growth is i.i.d., therefore the exogenously specified aggregate shocks are not what is driving predictability. Though this model is quite simple and used for qualitative intuition only, Favilukis and Lin (2015) solve a calibrated production economy with a similar channel for wage rigidity. That model is able to quantitatively match the data along both macroeconomic, and financial dimensions, including wage growth predicting stock returns.

For model generated data, we present results from regressions of stock returns at various horizons from $t+1$ to $t+s$ on wage growth realized at t:

$$R_{t+1,t+s} = \kappa_0 + \kappa_{\Delta W,s}\Delta W_t + \epsilon_{t+1,t+s} \qquad (3)$$

where $R_{t+1,t+s}$ is the cumulative, compounded, gross return from buying equity at t and selling it at $t+s$; and where $\Delta W_t = \frac{W_t}{W_{t-1}}$ is wage growth.[6] The results using labor share instead of wage growth as the predictor are also presented.

The model suggests that high (low) wage growth forecasts low (high) future return. This is because high (low) wage growth is associated with even higher (lower) output growth, resulting in lower (higher) operating leverage and less (more) risk for the firm. Furthermore, the coefficients rise with horizon, this is because sticky wages induce persistence in operating leverage.

Note that the key predictor is wage growth as opposed to rigidity itself. Even if the

[6]We do not take logarithms, although we have redone everything in terms of logarithms and the results look very similar.

degree of rigidity (μ) is constant, as long as it is positive, wage growth should negatively forecast stock returns. Of course rigidity itself may not be constant. As is discussed below, cross-sectional variation in rigidity is also used as an additional test of the labor leverage channel.[7]

Equation 3 is the key empirical specification. First this regression and versions of this regression with controls are run for aggregate U.S. stock returns. Then this regression will be run for a set of disaggregated assets. Two different sets of disaggregated assets are considered: U.S. industry returns, and U.S. state returns. This is referred to as the first stage regression; for each asset i, this first stage regression will compute a predictive slope $\kappa^i_{\Delta W,s}$.

Table 5 also shows predictability in a model with no rigidity ($\mu = 0$), high rigidity ($\mu = 0.95$), and high rigidity with high risk aversion ($\mu = 0.95$ and $\gamma = 13$). The degree of rigidity matters for the strength of predictability. In particular, if $\mu = 0$ then all predictive coefficients are exactly zero, as μ rises the predictability gets stronger (interestingly, the effect is quite non-linear). This implies that by using heterogeneity in rigidity across the disaggregated assets, we are able to have a second test of whether rigidity matters for stock returns. This test will be referred to as the second stage regression because it uses outputs from the first stage. In particular, this section runs the following cross-sectional regression:

$$\kappa^i_{\Delta W,s} \;=\; \lambda_0 + \lambda_\mu \mu^i + \epsilon^i_s \tag{4}$$

where μ^i is a measure of asset i's rigidity, to be described below and where $\kappa^i_{\Delta W,s}$ are the coefficients from the first stage. The slope of this regression should be negative $\lambda_\mu < 0$

[7] We also use time series variation in rigidity. Though these results are also consistent with the earlier intuition, they are much weaker statistically, perhaps because time variation in rigidity is more difficult to measure.

because more rigid industries should have stronger predictability.

The simple model is only meant to showcase the mechanism and the slopes in the baseline model are much smaller than in the data. However, the model with high rigidity and high risk aversion produces slopes of very similar magnitude to those in the data. The relationship between wage growth and expected excess stock returns in these three models can be seen graphically in Figure 1.

2.2. Extended model

The model above implies that wage growth should negatively forecast future stock returns. However, it also implies that labor share should positively forecast future stock returns, for exactly the same reason: operating leverage due to labor. In our empirical specification we focus on wage growth. Labor share is mostly insignificant. This section explains why this might be so. It presents an extended version of the original model in which the effect of labor share on stock returns is ambiguous because of two dueling channels. The first is the labor leverage channel described above, it suggests that labor share should positively forecast stock returns.

The second channel is described by Santos and Veronesi (2006). The intuition is that aggregate output (and therefore aggregate consumption) consists of multiple components, each affected by different shocks. When one component receives relatively positive shocks, it grows into a larger share in the consumption basket, and therefore it becomes more correlated with aggregate consumption and relatively more risky. If labor and dividends are the two components that make up consumption, then a positive shock to the labor share will cause dividends to become a relatively smaller part of the consumption basket, and therefore less risky. As a result, labor share should negatively forecast stock returns.

Which of these two channels dominates depends on the parameter choice. In the original model, wage growth negatively forecasts stock returns and labor share positively forecasts stock returns. The analysis here shows that with a reasonable extension of the original model, it is possible to have wage growth negatively forecasting stock returns, as before, but labor share also negatively forecasting stock returns. It is also possible to have labor share growth negatively forecasting stock returns (it positively forecasts stock returns in the simple model). For this reason, this paper focuses on wage growth as the key predictor in the empirical section, however this section also reports results when both wage growth and labor share are included as predictors.

In the extended model, as in the simple model, output is produced from labor N_t and labor-augmenting productivity. However, there is an additional component of output production which does not depend on labor and has its own shock, which is cointegrated with the labor-augmenting shock: $X_t = A_t x_t$.[8] There is also a stochastic process S_t which governs the share of each component.[9] Thus total output is:

$$Y_t = X_t S_t + (1 - S_t) A_t N_t^{\alpha} \tag{5}$$

where $S_{t+1} = \overline{S}(1 - \rho^S) + \rho^S S_t + \sigma^S \epsilon_{t+1}^S$ is an AR(1) process. We also allow x_t and $\frac{A_{t+1}}{A_t}$ to be AR(1) processes. This is one simple way of merging the Santos and Veronesi (2006) channel and the operating leverage channel.

The marginal product of labor has now changed, and the target wage is redefined so that it is again equal to the marginal product of labor: $W_t^* = \alpha(1 - S_t)A_t$. The average labor share is now $(1 - \overline{S})\alpha$; we update α so that the average labor share remains the same as in the simple problem. The problem is identical to the simple problem described earlier if $S_t = 0$. Although an analytic solution for the firm's value in this case is not

[8]The production function in equation 5 can be considered as a special case of a CES production function with the two inputs which are perfect substitutes.

[9]The stochastic process S_t can be thought of as a reallocation shock that affects redistribution of output to workers and shareholders, as in Rios Rull and Santaeulalia-Llopis (2010) and Lettau et al. (2015).

available, this problem is relatively straight forward to solve numerically. The appendix describes the numerical solution.

Predictability results from this model are also in Table 5. As before, wage growth negatively forecasts stock returns and the coefficients all increase with horizon, the intuition is the same as before. However, now labor share negatively forecasts stock returns at horizons up to 4 years. This is due to the Santos and Veronesi (2006) channel described above. With alternative parameters, it is possible to have labor share forecast stock returns negatively at longer horizons as well, but as will be shown below in Table 4, the switch from negative to positive after 4 years is consistent with the data (although none of the labor share coefficients appear significant). In this model, the persistence of S (share of output not dependent on labor) is crucial for having both wage growth (operating leverage channel) and labor share (Santos and Veronesi (2006) channel) negatively forecasting excess stock returns. If ρ^S is low enough, then the operating leverage channel dominates and labor share positively forecasts returns.[10]

Due to the Santos and Veronesi (2006) channel, our focus is on wage growth. However, this channel is about aggregate labor share affecting the aggregate pricing kernel and aggregate risk. It should be less relevant for disaggregated assets.[11]The appendix shows that at the state and industry level high labor share seems to be positively related to future returns, and makes future returns more responsive to wage growth; this lends further support for the relevance of operating leverage due to wage rigidities.

3. Data and Inference

This section first describes the inference method and then the data used in the paper.

[10] For both slopes to be negative, it is also possible to have a somewhat lower ρ^S if productivity growth $\frac{A_{t+1}}{A_t}$ is more persistent.

[11] It may still be relevant at the state level if risk sharing across states is incomplete, in which case it would be local consumption growth and local labor share mattering for risk. If there is also a home bias in financial portfolios (which is true in the data), then the Santos and Veronesi (2006) channel would hold state by state.

3.1. Inference

Because some of the statistics considered here are complicated and standard asymptotic inference may be difficult, this paper instead uses a bootstrap to do inference. In those cases where standard asymptotic inference is possible, we find that it is consistent with the bootstrap.

Suppose one regresses y_t on x_t and finds: $y_t = \widetilde{\beta} x_t + \epsilon_t$ where $\widetilde{\beta} > 0$ without loss of generality. There are two ways to use the bootstrap to test whether β is significantly different from zero. The first is to create simulated data sets where the average slope is $\widetilde{\beta}$ and then test how often the slope is above zero. For example one could create $\overline{y}_t = \widetilde{\beta} x_t + \epsilon_{t+s}$ for random s and then regress $\overline{y}_t$ on x_t to get a distribution for β. An alternative of the same approach is to jointly draw pairs (y_s, x_s) and then regress y on x.

The second approach is to create simulated data sets where the average slope is zero, and then test how often the slope is above $\widetilde{\beta}$. For example one could create $\overline{y}_t = y_{t+s}$ or $\overline{y}_t = \epsilon_{t+s}$ and then regress $\overline{y}_t$ on x_t to get a distribution for the slope centered at zero. For example Fama and French (2010) and Kosowski et al. (2006) use variations of this approach to test for persistence in mutual fund performance.

Our analysis could use either approach to test each individual regression in our empirical specification. However, because the data set is multi-dimensional and not all of the data end at the same time, it is important to keep the structure of the data in our bootstrap. This is straight forward with the second approach but difficult with the first. For example, suppose we wanted to compute the significance of the average slope across multiple forecasting horizons. Jointly draw $(R^1_{s+1}, ...R^{10}_{s+1}, \Delta W_s)$ is needed, but this would shorten our data set by ten years because the most recently available ten-year return is in 2001.

The second approach does not pose such problems as it allows us to keep the structure of the data set exactly as is. Our method uses a block bootstrap to ensure that possible autocorrelation in returns is present in the bootstrap; let the block size be b. We randomly pick a number a_1 between 1 and T, where T is the length of our data set. We then set $(\overline{R}_1, \overline{R}_2, ...\overline{R}_b) = (R_{a_1}, R_{a_1+1}, ...R_{a_1+b-1})$. The next step picks a new random number a_2 and set $(\overline{R}_{b+1}, \overline{R}_{b+2}, ...\overline{R}_{b+b}) = (R_{a_2}, R_{a_2+1}, ...R_{a_2+b-1})$. This method continues until it gets to $\overline{R}_T$. If at any time $a_i > T-b$ it continues setting $\overline{R}_t = R_s$ until it reaches $R_s = R_T$, then it "rolls over" and restarts at $s = 1$. It then uses $(\overline{R}_1, \overline{R}_2, ...\overline{R}_T)$ to compute long horizon returns just as it would with the real data, described in the next section. Note that it does not reshuffle the explanatory variables, just the returns. This allows us to create a fake data set with exactly the same structure as the original data set but which, by construction, has no return predictability. The reason it cannot do the same with the first approach is that it would need to jointly draw R_{a_1} and ΔW_{a_1-1} but the industry data set is too short and it would have to exclude the last ten years from the draw.

Using the approach described above, our analysis draws 1000 random samples of block size 10 (we have also experimented with alternative block sizes and the results look fairly similar). All of our statistics are computed for each of these samples. This gives us a distribution for each of our statistics. The distribution of each of the forecasting coefficients has a mean and median near zero, while the first stage results, where the fraction of coefficients with negative coefficients is reported, has a mean near 50%. For each statistic the reported p-value is the fraction of random samples in which the statistic's point estimate was as extreme, or more extreme than the point estimate in actual data. Thus, a p-value of 0.05 indicates that despite having a mean of zero, 5% of the time the coefficient was more negative than our estimated coefficient.

An additional benefit of the bootstrap approach is that it avoids Boudoukh et al. (2008)'s critique of much of the literature on long-horizon predictability. They point out that if the predictors are highly persistent then standard inference in long-horizon regressions with overlapping observations will be incorrect because longer horizons provide very little additional information. Although this is less of a problem for our exercise because wage growth is far less autocorrelated than standard predictors,[12] the bootstrap approach is not subject to this critique because even under the null of no predictability, the bootstrapped simulations retain the autocorrelation structure of the original data.

3.2. Data

Our analysis is restricted to the time period 1954-2014, this is despite the data for some of our analysis being available prior to 1954. The reason for starting in 1954 is that we believe that prior to 1954, massive government intervention in labor markets as a result of WW2 and the Korean War mutes our channel.[13] Our results are robust to starting after 1954; this can also be inferred from the sub-sample analysis in Table 3. However, starting before 1954 makes some of our results insignificant.[14] Table 2 presents the summary statistics of all variables used in the aggregate analysis.

[12]The 1954-2013 autocorrelation of aggregate wage growth is 0.46, compared to 0.55 for the price-earnings ratio, 0.91 for the price-dividend ratio, and 0.90 for cay.

[13]It is well known that during WW2 (1940-1945) there was a large movement of employees out of the private sector and into the military sector. As a result, private sector employment as a fraction of total employment fell by 12%, pushing up private relative to total wages by 3.6% and the labor share of the private sector by 15%. There was an exact reversal of these trends post-WW2 (1945-1947) with private sector employment as a fraction of total employment rising by 16%, private wages relative to total wages falling by 3.1%, and labor share in the private sector falling by 13%. The military buildup leading up to and including the Korean War (1947-1953) had a similar (though smaller) effect as WW2: private sector employment as a fraction of total employment fell by 3.8%, private sector wages relative to total wages rose by 1.2%, and labor share in the private sector rose by 7%. Post-1953 (including the Vietnam War), these quantities have remained much more stable; for example the biggest (in absolute value) 6 year changes in these quantities during 1954-2014 were 2.2%, 2.4%, and 3.3% respectively.

[14]Our mechanism implies that high wage growth is associated with a decrease in labor leverage and therefore low risk and low expected future returns. This mechanism is driven by productivity shocks in a world with rigid wages. Note that the relationship between wage growth and returns may be different if shocks other than business cycle shocks (for example to employment or bargaining power) are dominant. For example, in both WW2 and the Korean War build up, an increase in the size of the military resulted in high wage growth and high labor leverage for reasons unrelated to positive productivity shocks. At the same time valuations (such as the price/earnings ratio) were relatively low â€“ perhaps due to the high labor leverage or to the prospect of a long war. High subsequent realized returns followed, which is the opposite of what wage rigidity combined with business cycle shocks would predict.

3.2.1. Dependent variables

The left hand side in our regressions is the long horizon return. Our long horizon return is the total market equity return in excess of the risk free rate realized in year one through year s. It is computed by compounding gross monthly returns for the appropriate number of years.

$$R_{t+1,t+s} = \prod_{j=1,12\times s} R^e_{t+j} - \prod_{j=1,12\times s} R^f_{t+j} \tag{6}$$

The industry specific and state specific returns $R^i_{t+1,t+s}$ are defined in an analogous way. The aggregate and industry time series for R^e and R^f are available for 1929-2014, from Ken French's website:
http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html. The state returns are the value-weighted excess returns of the firms in CRSP/Compustat that are headquartered in the state, these are available 1950-2014.

3.2.2. Independent variables

In our first stage regressions the key explanatory variable is wage growth. Aggregate wage growth $\Delta W_t = \frac{W_t}{W_{t-1}}$ is defined to be the real wage in year t divided by the real wage in year $t-1$. The real wage is the nominal aggregate wage per full time equivalent employee[15] from the National Income and Product Accounts (NIPA) Table 6.6[16] divided by the consumption deflator from NIPA Table 2.3.4. Each industry's wage is defined in an analogous way using industry wage rates from the same NIPA Table as the aggregate

[15] We use wage per employee instead of per hour because this is the only measure available at the industry level. For aggregate results, we have tried wage per hour instead, results are slightly weaker but still very significant.

[16] On the NIPA website, all tables in section 6, including Table 6.6, are broken into 6.XA (1929-1948), 6.XB (1948-1987), 6.XC (1987-2000), and 6.XD (1998-2012). This is done because of changes in industry classifications in 1948, 1987, and 2000. In the appendix (Table A4) we describe how we merge 6.XA, 6.XB, and 6.XC and how we match this to Fama and French industry returns. Because the change in classifications in 2000 was quite drastic, we have decided to stop this data in 2000.

wage. The state wage is defined as the state's compensation (NIPA Table SA04) divided by its employees (from BLS).

Because of a change in industry classifications, the industry data is available from 1929 to 2000 only. Although industry data is also available post-2000, we were unable to reliably match enough industries between NIPA post-2000, NIPA pre-2000, and Fama and French industry returns to make extending the data set to 2014 worthwhile (note that for long horizon returns, this makes almost no difference because our analysis uses the 2000 wage growth to forecast return from for 2001-2010, which is available). There are a total of 26 matched industries, the matching is described in detail in Appendix Table A4. For states the data is available from 1950 to 2014, however not all states have data going back to 1954, as a result, there is a balanced panel of 40 states.[17]

In our second stage regressions, the explanatory variables are proxies for wage rigidity in a particular industry or state. The model suggests that high autocorrelation of wage growth and low volatility of wage growth should proxy for wage rigidity. It may be that the behavior of wage growth is influenced by the behavior of the underlying productivity shocks rather than rigidity. For this reason this section also reports results where the proxy is defined as the autocorrelation of the industry's wage growth relative to the autocorrelation of the industry's TFP, and similarly as the inverse of the volatility of the industry's wage growth relative to the inverse of the volatility of the industry's TFP. In addition to this, for the state level data another measure of wage rigidity is used. For each state and each presidential election we collect the fraction of the state's population that voted Democratic, this data is from http:/uselectionatlas.org; it includes all elections between 1952 and 2012 because our state level regressions start in 1954.

[17]The states are AZ, CA, CO, CT, DE, DC, FL, GA, ID, IL, IN, IA, KS, KY, LA, ME, MD, MA, MI, MN, MO, MT, NV, NH, NJ, NY, NC, ND, OH, OK, PA, RI, SC, TN, TX, UT, VA, WA, WV, and WI. One complication is that MI has no employees data for 1954 and 1955. We assume MI had the same rate of employee growth as IN and use the 1956 MI employees to back out the 1954 and 1955 employees. We choose IN because its employee growth had the highest correlation with MI.

Democrats are considered to be more labor friendly, which may lead to more bargaining power for employees, who may desire more wage rigidity as a form of insurance.

To compute an industry's TFP, one needs an industry's GDP, number of employees, and assets. The industry's GDP is defined as the sum of its National Income without Capital Consumption (NIPA Table 6.1), its Corporate Capital Consumption (NIPA Table 6.22) and its Non-Corporate Capital Consumption (NIPA Table 6.13). Industry assets are from NIPA Table 3.3ESI. Industry employees are from NIPA Table 6.5. TFP is then defined as the residual from a regression of the logarithm of GDP on the logarithm of assets and the logarithm of employees. Unfortunately, the quantities above are unavailable for some industries, we therefore use a coarser definition of industries to compute industry TFP, this coarser definition is in Appendix Table A4.

For some of the auxiliary statistics reported in the paper (appendix only) we also compute rolling measures of our rigidity proxies. The rolling measures are computed for the most recent 5 years, except for Democrats, which is just the state's Democrat share in the most recent presidential election.

There are several other variables which are used as controls in our analysis. These controls include the price-to-earnings ratio, the price-to-dividend ratio, and the consumption-to-wealth ratio (CAY).[18] We also use aggregate, industry and state labor share. Aggregate labor share is the nominal compensation of non-farm businesses divided by their GDP, both are from the Bureau of Labor Statistics. To compute industry labor share we divide an industry's compensation (NIPA Table 6.2) by its GDP (defined earlier). State labor share is computed as a state's compensation (defined earlier) divided by its GDP. State GDP is defined as personal income from NIPA Table SA1-3 (closely linked to GDP) because actual state GDP data does not start until 1963.

[18]The first two are from Robert Shiller's website: http://www.econ.yale.edu/ shiller/data.htm, the last is from Sydney Ludvigson's website: http://www.econ.nyu.edu/user/ludvigsons/data.htm

4. Results

This section presents the main empirical results on the time-series and the cross-sectional predictability of wage growth for expected returns, and the additional tests including conditional aggregate predictability and the Fama-MacBeth regression results.

4.1. Aggregate returns

This section tests whether aggregate wage growth negatively forecasts future aggregate excess equity returns. Table 3 presents the results of testing equation 3. Recall that we are regressing returns at horizons of 1-10 years realized at $t+1$ through $t+10$ on annual wage growth realized at t. Based on the intuition in the previous section, one expects wage growth to negatively forecast future returns. This is because when there are shocks to productivity in a world with rigid wages, negative wage growth is associated with rising operating leverage and increased risk.

Consistent with this intuition, our analysis finds that wage growth negatively forecasts returns. This relationship is significant and the predictability increases with horizon. Rather than focus on a particular horizon, our analysis will focus on the average coefficient across all horizons between one and ten years. Note that with our boot strap approach, it is straight forward to get p-values for most statistics, including this one. The p-value for this statistic is 0.01, indicating that there is a 1% chance of seeing a coefficient as extreme or more extreme than this one. The R^2's are also impressive, reaching 0.31 at a 10 year horizon.[19]

We perform several robustness tests. First, the results are split into two equal sized sub-samples. Although the relationships is stronger in the 2nd sub-sample, the results are significant in both sub-samples suggesting the relationship was consistently in the data

[19] Since there are only 60 years of data, the long horizon results must be taken with a grain of salt. For example for a 10 year horizon, we essentially only have 6 independent (non-overlapping) observations. Nevertheless, even the shorter horizon results are significant with non-trivial R^2's.

across during the full sample period. The p-value of both sub-samples being negative jointly is very small.

Second, two alternative measures of R^2 are computed. The Goyal and Welch (2008) measure (R^2_{GW} in Table 3) comes from forecasting returns in real time, by using only past data to compute the slope coefficient. It is defined as one minus the squared variation of the forecast error relative to the total squared variation.[20] These results are very similar to the original R^2. As with the average coefficient, the boot strap allows us to compute the p-value of this statistic as well; it is highly significant. An alternative is Hodrick (1992) measure (R^2_H in the Table 3), which assumes that returns and wage growth follow a first order vector autoregression and uses one period forecasts and errors to compute the implied long horizon forecasts, errors, and R^2's. By construction, at the one year horizon $R^2_H = R^2$, however at longer horizons R^2_H is much lower than the standard R^2 - perhaps because a first order vector autoregression is not a good description of returns and wage growth. However, despite the long-horizon R^2_H being relatively low, it is still significantly higher than would be expected if there were no predictability (the p-values are all below 10%).

Third, we run bivariate regressions where long horizon excess returns are regressed on wage growth and another candidate forecasting variable: $R_{t+1,t+s} = \kappa_0 + \kappa_{\Delta W,s}\Delta W_t + \kappa_{X,s}X_t + \epsilon_{t+1,t+s}$. These results are in Table 4. Three of the more well known forecasting variables are chosen: the price-dividend ratio, the price-earnings ratio (both based on Campbell and Shiller (1988)), and the consumption wealth ratio or CAY (Lettau and Ludvigson (2001). The correlation of wage growth with these variables is, respectively, 0.28, 0.16, and -0.29. Wage growth remains significant in each case.

Finally, this section includes labor share as an alternative forecasting variable, these

[20]We use the first 20 years to estimate the model. We then forecast returns each year using only coefficients estimated on past data to compute $R^2_{GW} = 1 - \frac{\sum(R-E_t[R])^2}{\sum(R-E[R])^2}$ where $E_t[R]$ is the model's forecast and $E[R]$ is the historical mean.

results are also in Table 4. The simple model suggests that wage growth and labor share are interchangeable for forecasting returns; they should be perfectly negatively correlated, and wage growth (labor share) should negatively (positively) forecast returns. The extended model showed that this need not be the case in general, and that labor share may even negatively forecast returns because it lowers the risk of the dividend stream, as in Santos and Veronesi (2006). Labor share appears insignificant for forecasting equity returns, with negative point estimates at the shorter horizons and positive at longer horizons.

4.2. Cross-sectional returns

Just as wage growth should forecast returns in aggregate data, it should similarly forecast returns for individual firms, industries, or regions. Because firm level wage data is not available, we repeat the exercise above at the industry level. Considering individual industries gives us an extra dimension along which to explore the relationship between the labor market and asset pricing. This is tested in two stages. The first stage runs time-series regressions for each industry analogous to the aggregate time series regressions in the previous section; the second stage compares coefficients from the first stage regressions to industry characteristics describing wage rigidity. We also repeat this for U.S. states. Doing this for states has two benefits: first, it is an additional and partially independent test of the importance of wage rigidity; second, it allows us to relate our wage rigidity measures to the state's political environment. Several additional tests are also performed, including Fama and MacBeth (1973) regressions; the main text will discuss some of these results, although the actual statistics are only presented in the appendix.

The variables are defined analogously to the aggregate variables but indexing everything by industry (or state) i, thus the left hand side variable is individual return, and the right hand side variable is the individual wage growth. Table 5 presents the results of these regressions for industries and Table 6 for states. Panel A presents the fraction of coefficients that are negative, the p-value of this fraction (probability of having this many negative coefficients if the true value was zero), and the average R^2. For industries, the lowest value is 73% (4 years), and across all horizons, 86% of the coefficients are negative; the p-value of the average is 0.01. States are even more supportive of the negative relationship between wage growth and future returns, with 94% of the coefficients being negative across all horizons. The average R^2 is 0.07 for industries and 0.09 for states. Not surprisingly, this is much lower than for aggregate returns as these assets are likely affected by individual shocks; nevertheless, these R^2's are relatively high considering this is disaggregated data. This exercise is referred to as the first stage.

The second stage tests whether the predictability pattern found in the first stage is stronger for industries (states) which have more rigid wages. Specifically, it uses equation 4 to compare the slopes from the first stage ($\kappa^i_{\Delta W,s}$) to measures of rigidity (μ^i). If the slope in this second stage regression is negative, then stronger forecastability is associated with more rigid industries and states.

We define wages as being rigid if the autocorrelation of wage growth ($AC(\Delta W)$) is high, or if the inverse of the volatility of wage growth is high ($1/VOL(\Delta W)$). These definitions are implied by the model in Section 2. It may be that the behavior of wage growth is influenced by the behavior of the underlying productivity shocks rather than rigidity. For this reason, there is an alternative definition where wages are rigid if the autocorrelation of wage growth is high relative to the autocorrelation of TFP (AC(ΔW) $- AC(\Delta TFP)$) or if the inverse of the volatility of of wage growth is high relative to the inverse of the volatility of TFP ($1/VOL(\Delta W) - 1/VOL(\Delta TFP)$). In addition, for states, a third measure of rigidity is defined as the average fraction of presidential ballots that were Democratic (DEM).[21] The intuition is that Democrats are

[21]The correlation of $AC(\Delta W)$ and $1/VOL(\Delta W)$ is 0.70 for industries and 0.32 for states. For states, the correlation of DEM with $AC(\Delta W)$ and $1/VOL(\Delta W)$ is 0.06 and -0.02 respectively.

considered more labor friendly, which may lead to more bargaining power for employees, who may desire more wage rigidity as a form of insurance.

These second stage results, in Panels B of Tables 5 and 6, suggest that the negative relation between wage growth and future returns is, indeed, stronger in industries and states which we define as more rigid. For both industries and states all point estimates are negative (the one exception being DEM at the 5-year horizon, which is positive but insignificant). Although not every single negative slope is significant, the majority are significant at the 10% level, with many having even stronger significance. Focusing on the average slopes across all horizons, the p-values are 0.01, 0.09, 0.05, and 0.06 for the four industry definitions of rigidity; they are 0.01, 0.02, and 0.11 for the three state definitions of rigidity. The relationship is economically significant as well, with R^2's all between 0.20 and 0.28 for industries, and between 0.10 and 0.17 for states.

4.2.1. Bivariate industry results

This subsection repeats the results in our main cross-sectional tests (Tables 5 and 6), however the regressions are now bivariate and include both wage growth and labor share as explanatory variables, with future return as the dependent variable. These results are in Tables 7 and 5.

As before, Panel A reports the fraction of wage growth slopes that are negative. As before, this fraction is high and significant for both industries and states. Panel A also reports the fraction of labor share slopes that are positive.[22] However, the number of positive slopes is insignificantly different from 50% for both industries and states.

[22]The reason we consider positive slopes as the baseline is that the Santos and Veronesi (2006) channel, which makes the sign of the slope on aggregate labor ambiguous, may be less relevant for disaggregated data. Recall that Santos and Veronesi (2006) suggest that aggregate labor share may, counter to the operating leverage intuition, negatively forecast stock returns. This is because as labor share rises, dividends become a smaller and therefore less risky part of aggregate consumption. This intuition is less likely to be relevant for an individual industry's labor share, thus we expect the operating leverage channel to matter more in the cross-section. As discussed in footnote 11, this may be less true for states if markets are segmented.

The 2nd stage results relate the wage growth slopes to proxies for rigidity (Panel B) and separately the labor share slopes to proxies for rigidity (Panel C). The wage growth results are quite similar to the univariate results in Tables 5 and 6: the relationship between slopes and rigidity is negative and mostly significant.

The industry results seem supportive of the operating leverage channel. The relationship between the slope on labor share and proxies of wage rigidity is positive and significant for all four proxies. Thus, labor share tends to positively forecast stock returns in industries that are more rigid. For state results, all three proxies for rigidity are not significantly related to the first stage slopes.

Thus, including labor share as a second predictor does not reduce the relevance of wage growth as a predictor of long horizon stock returns.

4.3. Additional tests

This section discusses several additional results, all tables with statistics for this set of results are in the Appendix.

4.3.1. Conditional aggregate predictability

The model in Section 2 implies that aggregate wage growth should forecast aggregate stock returns even if the degree of wage rigidity μ is not changing through time (as long as there is some rigidity). However, if rigidity itself is changing through time (for example due to exogenous changes in worker bargaining power, or in the demand for insurance that workers desire from employers) then predictability should be stronger in those times when rigidity is strongest - the intuition is the same as for the cross-sectional results in Section 4.2. We create a rolling time series of aggregate rigidity by computing the volatility and autocorrelation of wage growth over the previous five years at any point in time. Our analysis then run conditional regressions: $R_{t,t+s} = \kappa_0 + \kappa_\mu \mu_t + (\kappa_{\Delta W} + \kappa_{\mu\times\Delta W}\mu_t)\Delta W_t + \epsilon_{t,t+s}$. The proxies for rigidity are the 5-year, backward looking autocorrelation of aggregate wage growth, the inverse of the 5-year, backward looking volatility of aggregate wage growth, and the national Democrat share of the most recent presidential election.

The earlier intuition suggests that the relationship between wage growth and future returns should be negative on average ($\kappa_{\Delta W} + \kappa_{\mu\times\Delta W} E[\mu_t] < 0$), indeed it is negative and significant for all three proxies. Similar intuition suggests that the negative relationship should be stronger if rigidity is high ($\kappa_{\mu\times\Delta W} < 0$), the point estimates are negative but insignificant. Finally, if rigidity leads to more risk even independent of wage growth, then coefficient on rigidity alone ($\kappa_{\mu} > 0$) should be positive; the point estimates are positive but insignificant.

4.3.2. Fama-MacBeth industry results

This section provides an alternative look at cross-sectional predictability. Rather than the two stage approach, it uses Fama and MacBeth (1973) regressions. In particular, within each year, a cross-sectional regression of future industry return is run on industry wage growth ΔW_t^i and other industry characteristics μ_t^i. The characteristics are industry labor share LS_t, the 5-year rolling autocorrelation of industry wage growth $AC(\Delta W_t^i)$, the inverse of the 5-year rolling volatility of industry wage growth $1/VOL(\Delta W_t^i)$, and the Democrat share of the state vote in the most recent election DEM_t^i (state only).

The regressions take the form: $R^i_{t,t+s} = \kappa_{0,t} + \kappa_{\mu,t}\mu_t^i + (\kappa_{\Delta W,t} + \kappa_{\mu\times\Delta W,t}\mu_t^i)\Delta W_t^i + \epsilon^i_{t,t+s}$. The average coefficient over all years are reported. This analysis is separately done for industries and states. Our hypothesis is that the average dependence of expected returns on wage growth is negative, and that this dependence is stronger if labor share is high, or if wages are rigid. Furthermore, expected returns should be high when labor share is high or wages are rigid.

In the first, and simplest regression (first row) we regress future return $R^i_{t+1,t+s}$ on wage growth ΔW_t^i. All industry coefficients are rising in magnitude with horizon, and are negative and significant (the exception is the one-year horizon, which is positive and insignificant). Similarly, all state coefficients are negative and significant (the exception is the one-year horizon, which is negative and insignificant).

In the remaining regressions, the right hand variables are expanded to include wage growth, μ^i, and μ^i multiplied by wage growth, where μ^i one of the characteristics described above. In these remaining regressions, the result from the univariate regressions is unchanged: the average dependence of future returns on wage growth $(\kappa_{\Delta W,t} + \kappa_{\mu\times\Delta W,t}E[\mu_t^i])$ is negative and usually significant.

For industries, the point estimates of the conditional results are all as expected: a positive coefficient on the conditioning variable $(\kappa_{\mu,t})$ and a negative coefficient on the cross between wage growth and the conditioning variable $(\kappa_{\mu\times\Delta W,t})$. However, only $1/VOL_t(\Delta W)$ is significant with p-values around 0.08.

For states, the point estimates for DEM_t are as expected ($\kappa_{\mu,t} > 0$ and $\kappa_{\mu\times\Delta W,t} < 0$) and significant. For $AC(\Delta W_t)$ and LS_t the point estimates are also as expected but insignificant, and for $1/VOL(\Delta W_t)$ they go the wrong way, but insignificant.

Overall, these results are mostly supportive of our earlier results, however they are less significant than the main set of results. One reason that these results are weaker may be that we use the moving average, a fairly coarse measure, as our measure of rigidity.

5. Conclusion

Sticky wages are an important and widely studied topic in macroeconomics and labor economics. This paper shows that they also have important implications for finance. Sticky wages work like operating leverage, making the firm riskier. During bad times revenue falls, but if wages are sticky, the firm's costs fall by less, making the firm's cash flows more sensitive to aggregate shocks and riskier. This logic implies that falling wages should be associated with higher risk and should forecast high future returns.

This should be especially true in regions and industries with high labor share, or high wage rigidity.

We test the above predictions. Our empirical analysis shows that indeed, wage growth negatively forecasts returns for aggregate, industry, and state data. It also shows that this relationship is stronger when labor share is high, and in industries and states where wage rigidity is high. This research underscores the importance of including labor expenses in any consideration of risk, discount rates, and the cost of capital.

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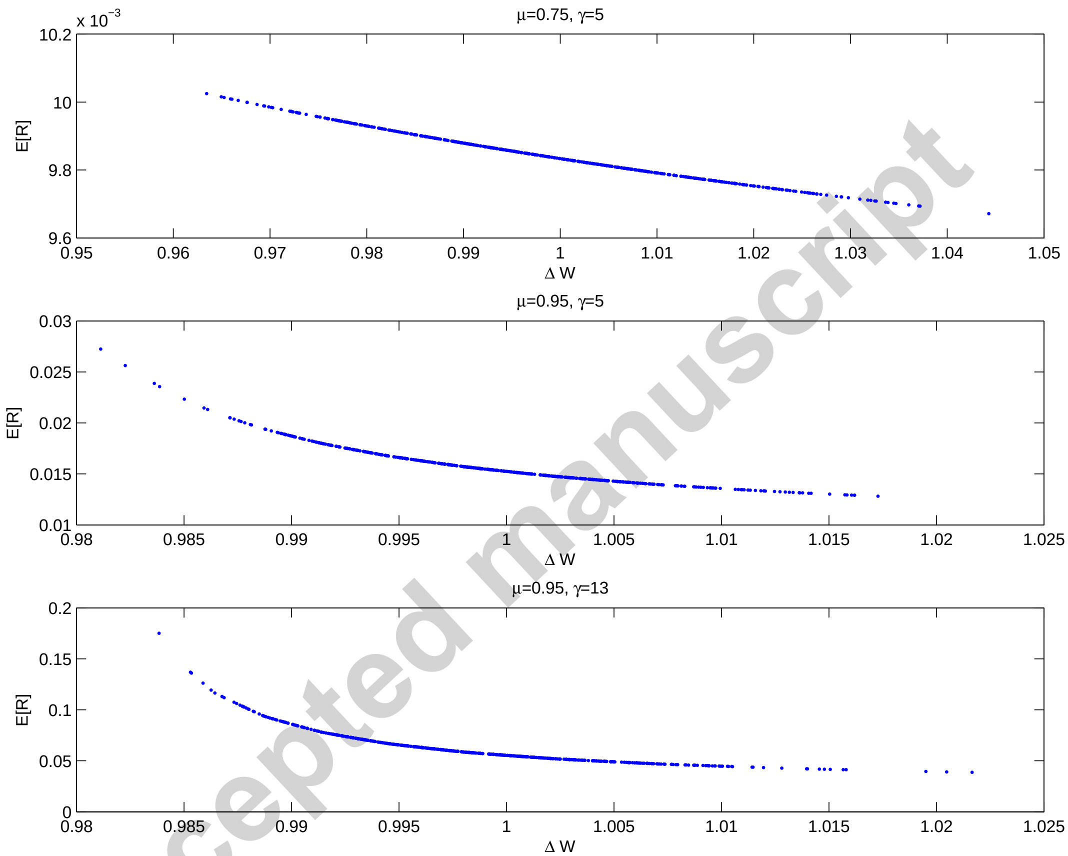

Figure 1: **Wage growth and expected return**
This figure plots the relationship between wage growth ΔW and expected return $E[R]$ in three different calibrations of the simple model described in the text. The top panel presents the baseline calibration ($\mu = 0.75$, $\gamma = 5$), the middle panel presents higher wage rigidity ($\mu = 0.95$, $\gamma = 5$), and the bottom panel presents both higher wage rigidity and higher risk aversion ($\mu = 0.95$, $\gamma = 13$).

Table 1:
Model

The top panel of this table presents the parameters from the simple and extended models. The bottom panel presents the slopes from regressions of future returns at various horizons (denoted by s) on wage growth for simulated data from each model, as well as the simple model with no rigidity ($\mu = 0$), high rigidity ($\mu = 0.95$), and high rigidity with high risk aversion ($\mu = 0.95$, $\gamma = 13$).

Model parameters

	μ	$\overline{S}$	$\alpha(1-\overline{S})$	γ	β	$\sigma(\frac{A_{t+1}}{A_t})$	$AC(\frac{A_{t+1}}{A_t})$	$\sigma(x)$	$AC(x)$	$\sigma(\epsilon^x)$	ρ^S
Simple Model	0.75	0	0.6	5	0.95	0.04	0	0	0	0	0
Extended Model	0.75	0.07	0.6	5	0.95	0.04	0.30	0.16	0.30	0.005	0.95

Predictability of returns: $R_{t+1,t+s} = \kappa_0 + \kappa_x x_t$

s	1	2	3	4	5	6	7	8	9	10
	Simple model: $\mu = 0$, $\gamma = 5$									
$\kappa_{\Delta W}$	0	0	0	0	0	0	0	0	0	0
κ_{LS}	0	0	0	0	0	0	0	0	0	0
	Simple model: $\mu = 0.75$, $\gamma = 5$									
$\kappa_{\Delta W}$	-0.0067	-0.0130	-0.0179	-0.0209	-0.0222	-0.0224	-0.0235	-0.0276	-0.0348	-0.0416
κ_{LS}	0.0037	0.0073	0.0100	0.0118	0.0125	0.0126	0.0132	0.0155	0.0194	0.0231
	Simple model: $\mu = 0.95$, $\gamma = 5$									
$\kappa_{\Delta W}$	-0.2607	-0.5275	-0.8013	-1.0825	-1.3728	-1.6693	-1.9756	-2.2932	-2.6172	-2.9514
κ_{LS}	0.0154	0.0248	0.0366	0.0479	0.0621	0.0739	0.0853	0.1015	0.1153	0.1346
	Simple model: $\mu = 0.95$, $\gamma = 13$									
$\kappa_{\Delta W}$	-2.4571	-5.7317	-9.0247	-13.2786	-18.2650	-22.8674	-28.7467	-35.0724	-42.6942	-52.3605
κ_{LS}	0.2269	0.5433	0.8415	1.2437	1.7153	2.1078	2.6341	3.1810	3.8541	4.7465
	Extended model									
$\kappa_{\Delta W}$	-0.0132	-0.0174	-0.0191	-0.0209	-0.0234	-0.0245	-0.0368	-0.0366	-0.0373	-0.0330
κ_{LS}	-0.0435	-0.0325	-0.0227	-0.0097	0.0040	0.0182	0.0352	0.0511	0.0697	0.0839

Table 2:
Summary statistics

This table presents the annual summary statistics for the variables used in the empirical analysis. The variables are wage growth, output growth, labor share, the price-to-earnings ratio, the price-to-dividend ratio, the consumption-wealth ratio, and the excess stock return. All variables are defined in the text.
newline

Panel A

x	W_t/W_{t-1}	Y_t/Y_{t-1}	LS_t	PE_t	PD_t	CAY_t	R_t
$E[x]$	1.0138	1.0313	0.6208	17.958	37.438	0.0002	0.0789
$\sigma[x]$	0.0136	0.0238	0.0210	8.663	16.454	0.0177	0.1874
$AC[x]$	0.467	0.186	0.914	0.546	0.914	0.900	-0.074

Panel B

	Y_t/Y_{t-1}	LS_t	PE_t	PD_t	CAY_t	R_t
W_t/W_{t-1}	0.523	0.233	0.162	0.285	0.034	0.194
Y_t/Y_{t-1}		0.059	-0.180	0.044	0.057	-0.051
LS_t			-0.165	-0.446	0.289	-0.140
PE_t				0.586	0.081	-0.173
PD_t					-0.022	0.108
CAY_t						0.137

Table 3:

Aggregate predictability

This table presents results from forecasting regressions of aggregate future stock returns at various horizons (denoted by s) on wage growth, where κ is the slope (equation 3). R^2_H is an alternative R^2 statistic described in Hodrick (1992) (equation 17), essentially it is the R^2 implied by assuming that returns and wage growth follow a vector autoregression. R^2_{GW} is an alternative R^2 statistic described in Goyal and Welch (2008) (equation 6), which is a goodness of fit in an out of sample forecast using only past information to estimate the model. The table also reports coefficients from breaking the sample in half, as well as the joint p-value of both sub-samples having negative coefficients. All p-values are obtained by a boot strapping procedure described in the text.

s	1	2	3	4	5	6	7	8	9	10	Avg
Full sample 1954-2014											
$\kappa_{\Delta W}$	-3.07	-8.42	-7.92	-11.56	-16.56	-19.54	-18.53	-26.26	-32.67	-44.32	-18.89
p-val	0.01	0.00	0.02	0.02	0.01	0.01	0.05	0.03	0.02	0.01	0.01
R^2	0.05	0.18	0.12	0.15	0.19	0.21	0.15	0.21	0.23	0.31	0.18
p-val	0.01	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00
R^2_H	0.05	0.05	0.04	0.03	0.03	0.02	0.02	0.02	0.02	0.02	0.03
p-val	0.08	0.07	0.08	0.08	0.09	0.09	0.09	0.09	0.09	0.09	0.08
R^2_{GW}	0.03	0.21	0.12	0.17	0.21	0.25	0.20	0.16	0.15	0.31	0.18
p-val	0.02	0.00	0.03	0.01	0.01	0.01	0.01	0.04	0.04	0.00	0.00
Sub-sample 1954-1984											
$\kappa_{\Delta W}$	-3.26	-6.36	-4.07	-4.78	-10.36	-15.36	-17.20	-22.42	-28.01	-36.45	-14.83
p-val	0.03	0.03	0.19	0.22	0.12	0.09	0.11	0.10	0.10	0.09	0.09
R^2	0.07	0.14	0.06	0.05	0.14	0.22	0.19	0.22	0.26	0.30	0.17
Sub-sample 1985-2014											
$\kappa_{\Delta W}$	-2.56	-11.84	-14.23	-23.66	-27.41	-26.56	-20.57	-33.20	-40.96	-60.21	-26.12
p-val	0.13	0.00	0.00	0.00	0.00	0.00	0.09	0.02	0.01	0.00	0.00
R^2	0.03	0.24	0.21	0.34	0.29	0.24	0.11	0.21	0.22	0.36	0.23
Sub-sample joint											
p-val	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00

Table 4:

Aggregate predictability, alternative factors

This table presents results from bivariate forecasting regressions of aggregate future stock returns at various horizons (denoted by s) on wage growth and one of several alternative predictive variables, where κ are the slopes (equation 3 with controls). The alternative forecasting variables are labor share, the price-earnings ratio, the price-dividend ratio, and the consumption wealth (CAY) ratio. All p-values are obtained by a boot strapping procedure described in the text.

s	1	2	3	4	5	6	7	8	9	10	Avg
Labor Share											
$\kappa_{\Delta W}$	-2.90	-8.14	-7.50	-11.31	-16.78	-20.32	-19.45	-27.10	-33.76	-44.66	-19.19
p-val	0.02	0.00	0.03	0.02	0.01	0.01	0.04	0.02	0.01	0.01	0.01
κ_{LS}	-0.47	-1.05	-1.73	-1.35	1.15	4.74	7.19	5.99	7.15	3.12	2.47
p-val	0.29	0.28	0.28	0.37	0.40	0.29	0.26	0.31	0.33	0.58	0.63
R^2	0.06	0.19	0.13	0.15	0.19	0.23	0.18	0.22	0.24	0.31	0.19
PE											
$\kappa_{\Delta W}$	-2.99	-8.48	-7.76	-11.47	-16.91	-19.72	-14.34	-21.31	-25.10	-34.23	-16.23
p-val	0.02	0.00	0.03	0.02	0.01	0.01	0.09	0.05	0.05	0.03	0.03
$100 \times \kappa_{PE}$	-0.08	0.05	-0.15	-0.09	0.34	0.17	-2.42	-2.89	-4.40	-5.75	-1.52
p-val	0.32	0.59	0.37	0.43	0.68	0.63	0.19	0.20	0.14	0.13	0.21
R^2	0.06	0.18	0.12	0.15	0.20	0.21	0.21	0.27	0.33	0.43	0.22
PD											
$\kappa_{\Delta W}$	-2.51	-7.60	-6.65	-9.56	-13.42	-15.18	-12.56	-19.46	-24.43	-34.59	-14.60
p-val	0.06	0.00	0.05	0.05	0.04	0.05	0.14	0.09	0.09	0.05	0.05
$100 \times \kappa_{PD}$	-0.16	-0.21	-0.33	-0.50	-0.78	-1.05	-1.44	-1.66	-2.05	-2.24	-1.04
p-val	0.09	0.20	0.23	0.22	0.19	0.19	0.17	0.19	0.19	0.22	0.19
R^2	0.07	0.20	0.14	0.19	0.25	0.29	0.27	0.32	0.35	0.41	0.25
CAY											
$\kappa_{\Delta W}$	-3.16	-8.44	-7.85	-11.21	-16.15	-18.73	-17.32	-25.08	-31.47	-42.83	-18.22
p-val	0.01	0.00	0.02	0.02	0.02	0.02	0.07	0.04	0.03	0.02	0.02
κ_{CAY}	2.15	4.22	6.66	9.32	12.05	15.09	16.43	17.91	19.58	18.95	12.24
p-val	0.03	0.04	0.04	0.05	0.06	0.07	0.10	0.13	0.15	0.20	0.10
R^2	0.10	0.26	0.25	0.31	0.35	0.40	0.32	0.35	0.35	0.39	0.31

Table 5:

Industry predictability and rigidity

Panel A presents the first stage of our industry tests. In particular, it reports the fraction of coefficients which are negative from regressions of industry stock returns (at various horizons, denoted by s) on industry wage growth (equation 3 for industries). It also reports the average R^2 across all industries, and the p-value of the fraction - that is the probability that the fraction of negative coefficients would be as or more negative if the true coefficient was zero. Panel B presents the second stage of our industry tests. In particular it presents the slope from regressing the coefficients from the first stage on one of four proxies of an industry's wage rigidity (equation 4). The proxies of rigidity are the autocorrelation of wage growth, the inverse of the volatility of wage growth, the autocorrelation of wage growth minus the autocorrelation of TFP growth, and the inverse of the volatility of wage growth minus the inverse of the volatility of TFP growth. All p-values are obtained by a boot strapping procedure described in the text.

s	1	2	3	4	5	6	7	8	9	10	Avg
Panel A: 1st Stage											
$\%\kappa_{\Delta W} < 0$	0.81	0.88	0.77	0.73	0.85	0.96	0.81	0.88	0.92	0.96	0.86
p-val	0.04	0.01	0.07	0.12	0.03	0.00	0.06	0.01	0.00	0.00	0.01
R^2	0.05	0.08	0.05	0.04	0.04	0.05	0.06	0.09	0.09	0.10	0.07
Panel B: 2nd Stage											
$AC(\Delta W)$	-1.44	-1.97	-2.92	-2.45	-2.20	-2.74	-1.75	-2.70	-2.57	-2.72	-2.35
p-val	0.18	0.14	0.07	0.12	0.13	0.10	0.20	0.10	0.11	0.10	0.09
R^2	0.11	0.18	0.30	0.26	0.22	0.29	0.13	0.23	0.22	0.25	0.22
$\frac{1}{VOL(\Delta W)}$	-3.49	-4.27	-2.63	-2.64	-2.91	-3.02	-2.60	-2.98	-2.71	-2.84	-3.01
p-val	0.03	0.02	0.10	0.11	0.09	0.09	0.13	0.08	0.10	0.09	0.05
R^2	0.24	0.35	0.24	0.22	0.24	0.32	0.23	0.26	0.24	0.29	0.26
$AC(\Delta W) - AC(\Delta TFP)$	-2.36	-3.05	-2.96	-2.95	-2.71	-3.16	-2.38	-3.11	-2.88	-2.97	-2.85
p-val	0.09	0.06	0.08	0.08	0.12	0.08	0.16	0.08	0.10	0.09	0.06
R^2	0.16	0.28	0.28	0.26	0.24	0.32	0.23	0.35	0.34	0.34	0.28
$\frac{1}{VOL(\Delta W)} - \frac{1}{VOL(\Delta TFP)}$	-2.91	-3.87	-2.00	-2.01	-2.30	-2.57	-2.32	-2.31	-2.20	-2.42	-2.49
p-val	0.04	0.02	0.13	0.14	0.12	0.09	0.11	0.10	0.11	0.09	0.06
R^2	0.19	0.32	0.16	0.14	0.17	0.28	0.20	0.19	0.18	0.23	0.20

Table 6:
State predictability and rigidity

Panel A presents the first stage of our state tests. In particular, it reports the fraction of coefficients which are negative from regressions of state stock returns (at various horizons, denoted by s) on state wage growth (equation 3 for states). It also reports the average R^2 across all states, and the p-value of the fraction - that is the probability that the fraction of negative coefficients would be as or more negative if the true coefficient was zero. Panel B presents the second stage of our state tests. In particular it presents the slope from regressing the coefficients from the first stage on one of three proxies of a state's wage rigidity (equation 4). The proxies of rigidity are the autocorrelation of wage growth, the inverse of the volatility of wage growth, and the Democrat share of total votes. All p-values are obtained by a boot strapping procedure described in the text.

s	1	2	3	4	5	6	7	8	9	10	Avg
Panel A: 1st Stage											
$\%\kappa_{\Delta W} < 0$	0.95	0.93	0.95	0.97	0.97	0.93	0.90	0.95	0.95	0.95	0.94
p-val	0.01	0.02	0.00	0.00	0.00	0.01	0.02	0.01	0.01	0.01	0.00
R^2	0.06	0.07	0.07	0.12	0.11	0.09	0.10	0.10	0.09	0.11	0.09
Panel B: 2nd Stage											
$AC(\Delta W)$	-3.51	-3.91	-3.91	-4.03	-3.60	-3.21	-2.59	-3.07	-2.81	-2.99	-3.36
p-val	0.01	0.01	0.00	0.00	0.01	0.02	0.05	0.03	0.05	0.04	0.01
R^2	0.10	0.21	0.24	0.22	0.20	0.17	0.12	0.19	0.13	0.10	0.17
$\frac{1}{VOL(\Delta W)}$	-1.06	-2.31	-2.80	-2.47	-2.14	-2.21	-1.65	-1.89	-2.17	-2.53	-2.12
p-val	0.22	0.05	0.01	0.03	0.05	0.06	0.12	0.09	0.06	0.03	0.02
R^2	0.03	0.10	0.16	0.16	0.13	0.13	0.07	0.09	0.10	0.13	0.11
DEM	-0.67	-1.56	-1.41	-0.75	0.56	-1.67	-3.50	-3.32	-3.20	-2.20	-1.77
p-val	0.30	0.15	0.19	0.30	0.69	0.17	0.04	0.03	0.04	0.09	0.11
R^2	0.01	0.07	0.07	0.01	0.01	0.06	0.22	0.27	0.20	0.10	0.10

Table 7:

Industry predictability and rigidity, bivariate

Panel A presents the first stage of our bivariate industry tests. In particular, it reports the fraction of wage growth (ΔW) coefficients which are negative, and of labor share (LS) coefficients which are positive from regressions of industry stock returns (at various horizons, denoted by s) on industry wage growth and labor share. It also reports the average R^2 across all industries, and the p-value of the fraction - that is the probability that the fraction of negative (positive) coefficients would be as or more negative (positive) if the true coefficient was zero. Panels B (wage growth) and C (labor share) present the second stage of our industry tests. In particular they present the slopes from regressing the coefficients from the first stage on one of three measures of an industry's wage rigidity. The measures of rigidity are the autocorrelation of wage growth, the inverse of the volatility of wage growth, the autocorrelation of wage growth minus the autocorrelation of TFP growth, and the inverse of the volatility of wage growth minus the inverse of the volatility of TFP growth. All p-values are obtained by a boot strapping procedure described in the text.

s	1	2	3	4	5	6	7	8	9	10	Avg
Panel A: 1st Stage											
$\%\kappa_{\Delta W} < 0$	0.81	0.88	0.77	0.69	0.85	0.88	0.77	0.81	0.85	0.96	0.83
p-val	0.05	0.02	0.08	0.15	0.02	0.01	0.07	0.05	0.03	0.00	0.01
$\%\kappa_{\Delta LS} > 0$	0.65	0.69	0.58	0.50	0.46	0.42	0.38	0.35	0.31	0.35	0.47
p-val	0.30	0.25	0.39	0.49	0.53	0.58	0.63	0.66	0.70	0.66	0.56
R^2	0.06	0.09	0.08	0.07	0.08	0.10	0.12	0.15	0.16	0.17	0.11
Panel B: 2nd Stage ΔW											
$AC(\Delta W)$	-1.47	-2.24	-3.43	-2.66	-2.33	-3.07	-1.92	-2.94	-2.86	-3.15	-2.61
p-val	0.20	0.11	0.04	0.10	0.13	0.08	0.19	0.10	0.10	0.07	0.07
R^2	0.11	0.23	0.37	0.29	0.25	0.35	0.17	0.27	0.27	0.31	0.26
$\frac{1}{VOL(\Delta W)}$	-3.42	-4.30	-2.61	-2.51	-2.80	-3.09	-2.76	-3.11	-2.81	-3.06	-3.05
p-val	0.04	0.02	0.10	0.12	0.11	0.08	0.10	0.07	0.10	0.08	0.05
R^2	0.25	0.38	0.22	0.19	0.19	0.27	0.21	0.25	0.23	0.30	0.25
$AC(\Delta W) - AC(\Delta TFP)$	-2.27	-3.10	-3.12	-3.06	-2.76	-3.37	-2.46	-3.21	-2.98	-3.25	-2.96
p-val	0.12	0.05	0.06	0.07	0.12	0.06	0.14	0.08	0.11	0.06	0.05
R^2	0.15	0.29	0.29	0.25	0.21	0.30	0.22	0.36	0.34	0.37	0.28
$\frac{1}{VOL(\Delta W)} - \frac{1}{VOL(\Delta TFP)}$	-2.91	-3.88	-1.84	-1.75	-2.04	-2.41	-2.17	-2.22	-2.10	-2.37	-2.37
p-val	0.07	0.02	0.16	0.18	0.14	0.10	0.11	0.10	0.11	0.09	0.05
R^2	0.20	0.34	0.14	0.11	0.12	0.21	0.16	0.16	0.15	0.22	0.18
Panel C: 2nd Stage LS											
$AC(\Delta W)$	0.14	0.54	0.82	0.76	0.84	1.07	1.23	1.33	1.46	1.46	0.97
p-val	0.45	0.33	0.23	0.25	0.22	0.16	0.11	0.09	0.06	0.06	0.17
R^2	0.00	0.01	0.03	0.02	0.03	0.05	0.07	0.08	0.10	0.10	0.05
$\frac{1}{VOL(\Delta W)}$	0.26	0.18	0.31	0.28	0.49	0.78	1.14	1.18	1.29	1.41	0.73
p-val	0.41	0.43	0.40	0.40	0.35	0.28	0.20	0.19	0.16	0.14	0.29
R^2	0.00	0.00	0.01	0.00	0.01	0.03	0.06	0.06	0.08	0.09	0.04
$AC(\Delta W) - AC(\Delta TFP)$	0.22	0.53	1.12	1.17	1.41	1.77	1.96	1.95	2.04	2.18	1.43
p-val	0.44	0.37	0.22	0.22	0.15	0.08	0.04	0.04	0.02	0.01	0.13
R^2	0.00	0.00	0.02	0.02	0.03	0.05	0.07	0.07	0.09	0.10	0.05
$\frac{1}{VOL(\Delta W)} - \frac{1}{VOL(\Delta TFP)}$	0.39	0.17	0.20	0.20	0.45	0.77	1.18	1.28	1.38	1.52	0.75
p-val	0.39	0.44	0.43	0.43	0.36	0.28	0.19	0.15	0.12	0.09	0.27
R^2	0.01	0.00	0.00	0.00	0.01	0.03	0.06	0.07	0.08	0.10	0.04

Table 8:

State predictability and rigidity, bivariate

Panel A presents the first stage of our bivariate state tests. In particular, it reports the fraction of wage growth (ΔW) coefficients which are negative, and of labor share (LS) coefficients which are positive from regressions of state stock returns (at various horizons, denoted by s) on state wage growth and labor share. It also reports the average R^2 across all states, and the p-value of the fraction - that is the probability that the fraction of negative (positive) coefficients would be as or more negative (positive) if the true coefficient was zero. Panels B (wage growth) and C (labor share) present the second stage of our state tests. In particular they presents the slopes from regressing the coefficients from the first stage on one of three measures of a state's wage rigidity. The measures of rigidity are the autocorrelation of wage growth, the inverse of the volatility of wage growth, and the Democrat share of total votes. All p-values are obtained by a boot strapping procedure described in the text.

s	1	2	3	4	5	6	7	8	9	10	Avg
					Panel A: 1st Stage						
$\%\kappa_{\Delta W} < 0$	0.95	0.90	0.95	0.97	0.97	0.93	0.90	0.93	0.93	0.93	0.94
p-val	0.01	0.04	0.00	0.00	0.00	0.01	0.01	0.01	0.01	0.01	0.00
$\%\kappa_{\Delta LS} > 0$	0.42	0.33	0.38	0.35	0.40	0.50	0.45	0.38	0.38	0.35	0.39
p-val	0.58	0.69	0.62	0.65	0.59	0.50	0.55	0.62	0.61	0.63	0.62
R^2	0.07	0.08	0.09	0.14	0.14	0.12	0.15	0.16	0.16	0.18	0.13
					Panel B: 2nd Stage ΔW						
$AC(\Delta W)$	-3.14	-3.79	-3.49	-3.94	-3.69	-3.11	-2.38	-2.95	-2.64	-2.70	-3.18
p-val	0.01	0.00	0.01	0.00	0.00	0.01	0.04	0.02	0.03	0.03	0.00
R^2	0.08	0.18	0.19	0.19	0.17	0.15	0.10	0.16	0.10	0.07	0.14
$\frac{1}{VOL(\Delta W)}$	-0.46	-1.70	-2.11	-1.96	-1.73	-1.86	-1.30	-1.49	-1.65	-1.94	-1.62
p-val	0.40	0.12	0.06	0.07	0.09	0.10	0.22	0.18	0.14	0.08	0.08
R^2	0.01	0.05	0.10	0.11	0.09	0.09	0.04	0.05	0.06	0.08	0.07
DEM	-0.75	-1.47	-1.24	-0.56	0.59	-1.42	-3.05	-2.94	-2.80	-1.76	-1.54
p-val	0.30	0.18	0.20	0.33	0.66	0.19	0.05	0.05	0.05	0.14	0.12
R^2	0.01	0.06	0.05	0.01	0.01	0.05	0.18	0.22	0.15	0.06	0.08
					Panel C: 2nd Stage LS						
$AC(\Delta W)$	-0.51	-0.15	0.14	0.39	0.11	0.35	0.17	0.33	0.29	0.34	0.15
p-val	0.38	0.46	0.41	0.34	0.41	0.33	0.40	0.36	0.40	0.40	0.40
R^2	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
$\frac{1}{VOL(\Delta W)}$	-2.25	-3.81	-0.16	0.36	-0.06	0.15	-0.14	0.02	-0.05	-0.02	-0.60
p-val	0.03	0.01	0.49	0.40	0.53	0.44	0.47	0.51	0.47	0.46	0.30
R^2	0.19	0.12	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.03
DEM	1.46	0.67	-0.43	-0.76	-0.41	-0.74	-0.59	-0.54	-0.37	-0.34	-0.20
p-val	0.13	0.33	0.35	0.26	0.34	0.26	0.31	0.33	0.38	0.39	0.42
R^2	0.04	0.00	0.00	0.01	0.00	0.01	0.01	0.00	0.00	0.00	0.01