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The Relationship Between Nominal Wage and Price Flexibility: New Evidence*

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Abstract: The frequencies at which prices and wages are adjusted, interpreted as price and wage flexibility, are key elements in workhorse models used for policy analysis. Yet, there is little evidence regarding the relationship between these two sources of nominal rigidities. Using two large and highly disaggregated price and wage microdata sets, this paper provides evidence that the industries changing more frequently wages reset prices more often. Once the frequency of wage adjustments is accounted for, the share of labor costs becomes less relevant in explaining the frequency of price changes, calling for a reinterpretation on previous findings that the labor share is a robust determinant of the frequency of price adjustments. The results in this study have implications for New Keynesian models' microfoundations, as their predictions have proven to be sensitive to the nominal rigidities assumptions.
Keywords: Nominal Stickiness; Micro Price Data; Micro Wage Data; Frequency of Adjustments
JEL Classification: E31, J31, C26

Resumen: La frecuencia en la que los precios y salarios se ajustan, interpretada como la flexibilidad de precios y salarios, es un elemento central en modelos comúnmente utilizados para el análisis de políticas económicas. Sin embargo, existe poca evidencia sobre la relación entre estas fuentes de rigideces nominales. Utilizando bases de microdatos de precios y salarios desagregadas, el presente documento provee evidencia de que las industrias que ajustan más frecuentemente salarios son aquellas que cambian sus precios más a menudo. Asimismo, una vez que se controla por la frecuencia de cambio de salarios, la proporción de costos de mano de obra se vuelve menos relevante en explicar la frecuencia de ajustes de precios, haciendo importante reinterpretar los resultados de estudios previos que encuentran que el costo de mano de obra es un determinante robusto de la frecuencia de cambio de precios. Los resultados de este estudio tienen implicaciones para los microfundamentos de los modelos Neo-Keynesianos, pues sus predicciones han mostrado ser sensibles a los supuestos sobre rigideces nominales.
Palabras Clave: Rigideces Nominales; Microdatos Precios; Microdatos Salarios; Frecuencia de Cambios

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1 Introduction

Does wage flexibility drive price flexibility? Do industries resetting wages more frequently change prices more often? Based on two separate and highly disaggregated worker and product-level datasets from Mexico, we look at the fraction of wage and price adjustments at industry-level and study them under a panel structure. To the authors' knowledge, this is the first paper to use such extensive quantitative datasets to link together wage changes and price adjustments. Our panel of industries includes information from prices and wages in Mexico from 2011 to 2018 and allows addressing unobserved heterogeneity at the industry level. We interpret the flexibility of wage and price adjustment in terms of the observed proportion of goods and workers that receive a price or wage change.[1]

Our findings suggest that price flexibility is indeed affected by wage flexibility. There is a positive effect of the frequency of wage adjustments on the frequency of price changes. On average, an increase of 1 p.p. in the fraction of workers receiving a wage adjustment in the year is translated into a 1.2 p.p. raise in the frequency of price changes. We alleviate potential endogeneity issues by using an instrumental variable approach. The instrument is the share of minimum wage workers in a given industry. Intuitively, as minimum wage workers normally receive only one wage adjustment in the year, the share of minimum wage workers affects wage flexibility and price flexibility only through the proportion of wage adjustments. Using this as an instrument we are able to avoid attributing causal status to wage frequency that might derive from a third factor influencing both price and wage frequencies.

The majority of small to medium scale New Keynesian DSGE models use the Calvo (1983) framework. The Calvo framework assumes price- and wage-setters face a constant probability of adjustment. As there is a continuum of price- and wage-setters, the probability of adjustment is mapped as the fraction of price- and wage-setters adjusting their prices and wages, respectively, period by period.[2] However, there is no theoretical mechanism for the

[1]The literature review by Klenow et al. (2010) highlights numerous studies using the frequency of price adjustments as a measure of price flexibility. This is the norm throughout this paper.

[2]The Calvo framework assumes price- and wage-setters adjust their prices and wages to its optimal level. Hence, it does not account for the size of adjustment. We follow this approach in the paper and focus on the

frequency of wage changes to influence price-setting in these models. Following Erceg et al. (2000), most models assume that there is a continuum of labor types which are combined by aggregation to be a single labor input to firms in all sectors/industries, in the same way the intermediate monopolistically competitive goods are combined into a single output.[3] Hence, there is no industry-specific link between wages and prices. Whilst this may be a convent theoretical simplification, in practice wages and much of the labor input are industry specific. We link wages and prices in our two datasets.

We are able to explore the extent to which downward nominal rigidities in wages might be greater than for prices. On the one side, employees dislike receiving wage cuts which prevents employers from decreasing wages.[4] On the other side, it is easier for price-setters to engage in sales strategies which would lead to roughly the same number of price increases and decreases. Hence, concerns arise in whether the positive relationship is driven by industries with more frequent wage increases but with prices jumping around reference prices. Therefore, we estimate our model focusing on the frequency of wage and price increases only. The main qualitative results are confirmed for this case. Furthermore, since our dataset reports whether a price is considered a sale/end-of-sale price, we are able to filter out sales-related price changes. We also find evidence that the frequency of wage changes increases the frequency of price changes when sales are excluded.

Peneva (2011), Vermeulen et al. (2012) and Álvarez et al. (2006) document an inverse relationship between the frequency of price adjustments and the share of labor costs for the US and some EU economies. As Klenow et al. (2010) summarises, labor-intensive sectors adjust prices less frequently, potentially because wages adjust less frequently than prices. When we do not control for the frequency of wage changes, our data supports this result. However, once the frequency of wage adjustment is included in the econometric framework, labor share becomes statistically insignificant. In contrast, the effects of frequency of wage

fraction of price and wage changes only.

[3]Smets and Wouters (2003) or Galí (2015) provide a detailed description of models featuring monopolistic competition in both the goods and labor markets using à-la-Calvo price- and wage-setting.

[4]See, for instance, Le Bihan et al. (2012), Barattieri et al. (2014) and Sigurdsson and Sigurdardottir (2016). Employers might also be impeded to incur in wage cuts by local regulations. That is the case for Mexican employers.

adjustment are statistically significant in our different specifications. Therefore, our results might call for a reinterpretation of previous findings in the literature.

Our IV estimation using the share of minimum wage workers as instrument relies on the fact that minimum wage workers normally receive only one wage adjustment in the year, while non-minimum wage employees generally receive more than one wage revision in the year. Our instrument would fail to generate exogenous variation on the frequency of wage changes when, for instance, both minimum wage and non-minimum wage workers receive roughly the same number of adjustments on the same year. In fact, that was the case for minimum wage workers in certain areas in Mexico in 2012, 2015 and 2017.[5] Hence, our benchmark specification does not consider these years.

The literature on price and wage setting using microdata has been growing rapidly in the last decade. On the one hand, the price literature has reached a consensus about the great degree of heterogeneity on price flexibility across different sectors/industries in the economy. See, among others, Bils and Klenow (2004), Álvarez et al. (2006), Dixon and Tian (2017). Likely determinants of such sectoral heterogeneity have been studied by the Inflation Persistent Network (IPN). One of the conclusions of IPN's research was that wages were among the most important factors determining the timing to reset prices.[6] In the same line, and importantly for this research, Peneva (2011) and Vermeulen et al. (2012) find that industries with a higher share of labor costs in total costs make less frequent price adjustments, potentially resulting from the fact that wages adjust less frequently than prices.[7] Our analysis empirically assesses whether wage flexibility contributes to price flexibility. To our knowledge, no previous study has systematically investigated this relationship. The analysis that is closest

[5]Prior 2012, there were three different minimum wage rates in the Mexican economy. In 2012 and 2015, there were extemporaneous minimum wage adjustments (in addition to the annual increase) affecting well defined geographical areas catching up with the highest minimum wage rate. By late 2015 there was a single minimum wage rate nation-wide. Moreover, the 2018 minimum wage increase was brought forward to late 2017. Thus, 2017 also saw two minimum wage adjustments.

[6]These conclusions lead to IPN's follow up project: Wage Dynamic Network.

[7]This is "Fact 10: Price changes are linked to wage changes" in the *Handbook of Monetary Economics* by Klenow et al. (2010). Citing work by Peneva (2011) and Vermeulen et al. (2012), this stylised fact is reached by looking at the (indirect) relationship between price changes and wage changes via the share of labor costs. Our paper uncovers quantitatively if price changes are driven by wage changes for the first time to the best of our knowledge.

to our approach, and makes the most progress in studying jointly price and wage setting, is Druant et al. (2012) from the Wage Dynamic Network (WDN). The authors find firms tend to concentrate wage changes in a specific month, mostly January in a majority of European countries, and that prices change when wages change in general. The main weakness, however, in Druant et al. (2012) is the descriptive approach they follow due to the qualitative data from categorial questionnaires they have at hand. In contrast, we use nearly ten years of quantitative product- and worker-level data, which is then analysed using a panel IV estimation at industry level.

On the other hand, studies by Sigurdsson and Sigurdardottir (2016) and Le Bihan et al. (2012) are important references analysing wage-setting determinants. Importantly for this study, Gautier et al. (2016) documents that high-wage workers tend to receive more frequent wage adjustments than low-wage workers in France. We find a similar pattern in Mexico's labor market and exploit this critical labor market characteristic in our IV strategy.

The contribution of our results to the nominal rigidities literature is twofold. First, we assess the role of wage flexibility driving price flexibility. Despite the fact wages greatly contribute to the encompassed value added in final prices, wage flexibility is yet to be analysed as a determinant of price flexibility in a formal econometric setting.[8] Second, it provides evidence that enriches the design and calibration of microfounded New Keynesian DSGE models with nominal rigidities. Research by Carvalho (2006), Kara (2015), Dixon and Le Bihan (2012) and Solórzano and Dixon (2019) highlight that properly modelling the heterogeneity on the frequency of price and wage adjustments (as observed in microdata) alters aggregates' dynamics in DSGE models. Indeed, Solórzano and Dixon (2019) poses the idea that a positive relationship between the two nominal frictions (price and wage rigidities) would not be trivial for aggregate dynamics. They show that a multi-sector economy, calibrated under a positive relationship between prices and wages, exacerbates the real side effects of nominal shocks.[9]

[8]As mentioned above, Druant et al. (2012) use a narrative approach to highlight that managers in EU firms consider the timing of wage revisions, among other factors, for the timing of price adjustments.

[9]Solórzano and Dixon (2019) devote greater effort on presenting the multi-sector DSGE and the implications of the likely positive relationship of prices and wages. They show, as motivation for their work, some descriptive evidence of this relationship by fitting a cross-section of industries using a standard OLS estimation. Instead, this paper assesses the causal relationship of wage flexibility on price flexibility using a panel IV framework.

This paper is organised as follows. Section 2 discusses the empirical strategy followed in the paper and describes the data. Section 3 reports results. Finally, Section 4 concludes.

2 Econometric Framework

The section below describes the empirical strategy, as well as the data we rely on assessing whether wage flexibility results in price flexibility. We start by presenting the panel specification. Then, we explain why endogeneity issues might arise and the instrumentation behind, and we finish detailing some descriptive statistics from our datasets.

2.1 Empirical Strategy

In line with papers exploiting the industry-level heterogeneity to study potential determinants of the frequency of price adjustments, we regress the frequency of price adjustments on the frequency of wage adjustments and further industry characteristics.[10] Our framework is

$$FreqPriceAdj_{k,t} = \alpha + \beta_1 FreqWagesAdj_{k,t} + \beta_2 X_{k,t} + \gamma_k + \gamma_t + \varepsilon_{k,t} \tag{1}$$

where subscripts k and t represent industry and year respectively. $FreqPriceAdj_{k,t}$ is the frequency of price adjustments and $FreqWagesAdj_{k,t}$ is the frequency of wage adjustments. Described in greater detailed below, $FreqPriceAdj_{k,t}$ ($FreqWagesAdj_{k,t}$) is calculated as the average in year t of the fraction of monthly price (wage) changes in industry k. $X_{k,t}$ are a set of time-varying industry characteristics. These industry characteristics are the share of labor costs, a proxy aiming at controlling on how easy it is for certain sectors to adjust their

[10] See, among others, Álvarez et al. (2006), Álvarez et al. (2010), Cornille and Dossche (2006) for similar econometric approaches regressing frequency of price changes on industry characteristics. The literature usually calculates industry characteristics using statistics drawn from Input-Output tables. The closest the literature gets is to include the share of labor costs. No previous study has investigated the role of wage rigidities on price rigidities, mainly due to data limitations, and we are able to uncover this relationship by analysing two independent price and wage datasets at industry level.

labor costs and energy intensity.[11] γ_k is a set of industry fixed effects controlling for the size of price adjustment and unobserved heterogeneity at industry level; and γ_t is a set of time fixed effects addressing common shocks to all industries at different points in time.

As presented in great detail in the data subsection, the frequency of wage adjustments is calculated using information from formal workers only. Hence, our benchmark results should be seen as the effect of formal workers' wage changes on price adjustments.[12]

Estimating the econometric framework specified in Equation 1 using OLS would produce biased results due to two main reasons likely to be present in our context. First, our specification might suffer from reverse causality. For instance, suppose households set their wages only after price-setters have decided the fraction of new prices in the economy. Second, there is an omitted variable bias concern. Failing to address this issue might attribute causal status to the wage adjustment frequency that might derive from a third factor influencing both price and wage frequencies. For instance, one can think of a productivity shock affecting both price and wage frequencies of adjustments.[13] As long as the omitted variable is temporal over our sample and affecting all industries, time fixed effects in our specification should ameliorate this problem to a great extent. Alternatively, industry fixed effects accounts for industry-specific shocks if they prevail throughout our panel.

We address both sources of endogeneity by instrumenting the frequency of wage adjustment with the share of Minimum Wage (MW) workers by industry in a year. The intuition on the instrument and tests regarding its relevance is as follows. On the relevance aspect, the share of MW workers is likely to have a predictive power over the frequency of wage adjustment because, historically, these workers have received only one wage increase per year.[14]

[11] The proxy on how easy it is for certain sectors to adjust their labor costs is defined as the standard deviation of the detrended and seasonally adjusted labor force in industry k over year t. See Subsection 2.2 for more on the calculation of this covariate.

[12] Note that informality, along with other input shares in the production function, is unlikely to vary substantially over our sample years. Therefore, industry fixed effects might ameliorate the bias stemming from the lack of informal workers in our sample. Nonetheless, in one of the robustness checks, we go to the data and include a covariate controlling for the degree of informal workers. The qualitative conclusions do not change whatsoever.

[13] Imagine a natural disaster or a fiscal stimulus generating greater demand for some or all industries' output, which in turn boost resetting prices and wage revisions.

[14] Notable exceptions are 2012, 2015 and 2017 when minimum wage rates were adjusted more than once within a single year.

Such sole increase implies a frequency of wage adjustment of 8.3% or $\frac{1}{12}$ for minimum wage workers, where the 12 in the denominator reflects the fact that the panel is formed of yearly averages calculated using monthly observations. As the share of minimum wage workers increases in industry k, $FreqWagesAdj_{k,t}$ would converge to 8.3%. On the contrary, as minimum wage workers decreases in industry k, $FreqWagesAdj_{k,t}$ would rise from 8.3%. The stylised fact that minimum wage workers tend to receive less frequent wage adjustments than non-minimum wage workers is supported by our data and discussed in great detail below.

This intuition can be summarised in an analytical expression where $FreqWagesAdj_{k,t}$ is seen as the weighted average of the frequency of wage adjustment of those earning the minimum wage and those earning above the minimum wage, $FreqWagesAdj_{k,t}^{MW}$ and $FreqWagesAdj_{k,t}^{NoMW}$, respectively. That is,

$$\begin{aligned} FreqWagesAdj_{k,t} &= \alpha_{k,t}^{MW} FreqWagesAdj_{k,t}^{MW} + \left(1-\alpha_{k,t}^{MW}\right) FreqWagesAdj_{k,t}^{NoMW} \\ &= \alpha_{k,t}^{MW} \left(FreqWagesAdj_{k,t}^{MW} - FreqWagesAdj_{k,t}^{NoMW}\right) \ ... \\ &\qquad ... + FreqWagesAdj_{k,t}^{NoMW} \end{aligned}$$

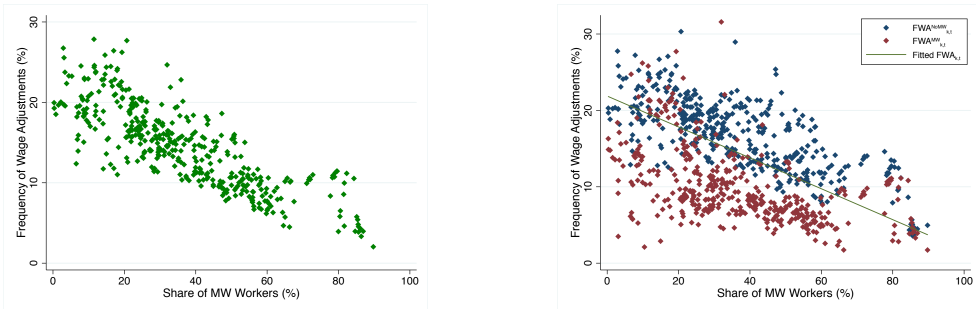
where $\alpha_{k,t}^{MW}$, the share of minimum wage workers at industry k in year t, is our proposed instrument. Thus, the relationship between the instrument $\alpha_{k,t}^{MW}$ and the endogenous variable $FreqWagesAdj_{k,t}$ reveals the gap between non-minimum wage and minimum wage frequencies of adjustments,

$$\frac{\partial FreqWagesAdj_{k,t}}{\partial \alpha_{k,t}^{MW}} = FreqWagesAdj_{k,t}^{MW} - FreqWagesAdj_{k,t}^{NoMW} \tag{2}$$

We are able to shed further light in the relevance of our instrument on $FreqWagesAdj_{k,t}$ by looking at the data. First, if $FreqWagesAdj_{k,t}^{MW} \approx \frac{1}{12} < FreqWagesAdj_{k,t}^{NoMW}$, we might expect $\frac{\partial FreqWagesAdj_{k,t}}{\partial \alpha_{k,t}^{MW}}$ to have a negative sign. Indeed, Figure 1a illustrates a downward slopping relation between $FreqWagesAdj_{k,t}$ and $\alpha_{k,t}^{MW}$ using all k-t observations in our panel.[15] Moreover, Figure 1b shows that $FreqWagesAdj_{k,t}^{MW}$ (depicted as red diamonds) are,

[15]These statistics are described and computed in Subsection 2.2 in great detail.

Figure 1: Frequency of Wage Adjustments and Share of MW Workers.



(a) Industry-Year observations

(b) Industry-Year observations by income.

Note: The two panels plot the frequency of wage adjustment (vertical axis) and the share of minimum wage workers (horizontal axis) per industry per year. Panel 1a, left, depicts the pool of observations in our panel of industries. Each diamond represents one industry in one year. The height for each diamond is the frequency of wage adjustment, whereas the width is the share of minimum wage workers. Panel 1b, right, disaggregates the frequency of wage adjustments into the frequency of wage adjustments for non-minimum wage workers (blue diamonds) and minimum wage workers (red diamonds). Thus, each industry is represented by two diamonds sharing the same width, the share of minimum wage worker, which is a within industry characteristic.

in general, below $FreqWagesAdj_{k,t}^{NoMW}$ (depicted as blue diamonds). Furthermore, Table 1 reports aggregates arising from Figure 1b. Importantly, the difference between the first and second rows of column one shows that $FreqWagesAdj_{k,t}^{MW}$ is roughly 6 p.p. less than $FreqWagesAdj_{k,t}^{NoMW}$. The fact that workers in higher income deciles receive more frequent wage adjustments than workers in the lower deciles is not something unique to the Mexican economy. Gautier et al. (2016) have documented similar patterns for French workers. In sum, our data supports the idea of a negative sign in Equation 2.

Second, if $FreqWagesAdj_{k,t}^{MW} \approx FreqWagesAdj_{k,t}^{NoMW}$, Equation 2 implies that our instrument would no longer be relevant. Table 1 highlights that $FreqWagesAdj_{k,t}^{NoMW}$, on average, is about 50% greater than $FreqWagesAdj_{k,t}^{MW}$, where the latter is normally dictated by the annual (single) MW update. Figure 1b also makes this case, $FreqWagesAdj_{k,t}^{NoMW}$ is nearly half $FreqWagesAdj_{k,t}^{MW}$. Thus, years in which MW workers receive more than one wage adjustment might lead to $FreqWagesAdj_{k,t}^{MW} \approx FreqWagesAdj_{k,t}^{NoMW}$, therefore, both terms on the right hand side in Equation 2 would cancel out, leading to a potential weak instrument estimation. There are three years in our sample when that might be the case: 2012, 2015 and 2017.

Table 1: Average Frequency of Wage Adjustment by Income and Share of MW Workers

	Frequency of Adjustments		Frequency of Increases		Share of Workers
	Mean	Std. Dev	Mean	Std. Dev	Mean
	(1)	(2)	(3)	(4)	(5)
Less than 1.5 MW	10.96	5.10	9.45	4.30	36.63
More or equal than 1.5 MW	17.04	4.60	13.57	3.58	63.37
Overall	15.05	4.97	12.23	3.79	100.00

Note: This table shows the frequency of wage adjustment by income level. Each entry in the table is calculated, first, at industry level and then as unweighted averages across industries. More specifically, workers in a given industry are split into two bins: bin one contains those earning less than 1.5 minimum wages, while bin two considers those earning more than 1.5 minimum wages. Then, the fraction of wage changes is calculated for each bin for all industries. Finally, in order to calculate the average frequency of wage adjustment of those earning less than 1.5 minimum wages, for instance, we compute the unweighted average of bins one across industries. Similarly, the standard deviation of those earning less than 1.5 minimum wages is calculated as the unweighted standard deviation of the frequency of wage adjustments of bins one across industries. The last row follows the same steps just described but without splitting workers by income level. Note that the minimum wage level changes over time and had different rates per region. Special care is taken in order to classify who was above and below the 1.5 minimum wage threshold depending the worker's location (e.g. there were three MW regions in early 2011 but only one MW region by late 2018) and year of observation (e.g. the MW did not remain flat over our sample period). The dataset reports wages from 2011 to 2018. For more details on the wage dataset, see Subsection 2.2.

The first two of them, 2012 and 2015, are related to a policy intervention unifying the minimum wage rate nation-wide.[16] As the first episode in 2012 affected only a handful of locations (about 2% of Mexican municipalities), $FreqWagesAdj_{k,t}$ did not exhibit any dramatic change relative to previous years. See Figure 2 and the lack of any abrupt variation in 2012. The second episode in 2015 affected more than 95% of Mexican municipalities. A humped shape in 2015 can be seen in Figure 2 as a result of the unification policy. The two minimum wage adjustments in 2015 would lead to weak instrumentation as Equation 2 shows. Thus, we discard 2015 from our benchmark panel IV specification.

The third year where there are two MW adjustment on the same year and special attention is required is 2017. In 2017, the annual minimum wage increase corresponding to 2018 was brought forward to November 2017. Again, due to the double minimum wage increase in 2017, $\frac{\partial FreqWagesAdj_{k,t}}{\partial \alpha^{MW}_{k,t}}$ might be close to zero. As the second MW revision was fairly late

[16]Before 2012, there were three different minimum wage zones in Mexico. A new policy unifying MW rates in Mexico took place in two independent episodes (2012 and 2015) affecting two independent geographic regions.

in the year and prices are not adjusted promptly, it is likely that wage changes are reflected onto prices in 2018. Thus, instead of simply dropping out 2017 (as with 2015), we address this issue by imputing the late 2017 minimum wage increase as if it would have happened in 2018. Observed and imputed values are shown in Figure 2.[17] Nonetheless, we report results using both observed and imputed data in Section 3.

Regarding the contemporaneous price flexibility resulting from wage flexibility assumed in Model 1, and not allowing any lasting effect i.e. lags, two main reasons arise. On the one hand, dealing with serial correlation arising from lagged covariates would further shortened the panel. On the other hand, wage adjustments tend to happen early in the year and goods' prices tend to accommodate shocks fairly quickly, while service prices are also adjusted early in the calendar year.[18] Thus, we believe the contemporaneous relationship asserted in the panel reflects well the wage effects on prices.

With respect to the nature of $\varepsilon_{k,t}$ in Equation 1, we assume the error terms are correlated within broad industry categories. This assumption comes from the fact that industries either have overlapping production lines and/or some products act as substitutes between industries (e.g. food-related industries). Described in greater detail in the following subsection, the (70) industries in our final sample are clustered into six broad categories. However, inference from the cluster-robust variance matrix estimator can be misleading when there are only six clusters and when they are not homogeneous enough in size.[19] As inference using cluster-robust variance estimators can lead to over-rejection when the number of clusters is small, we con-

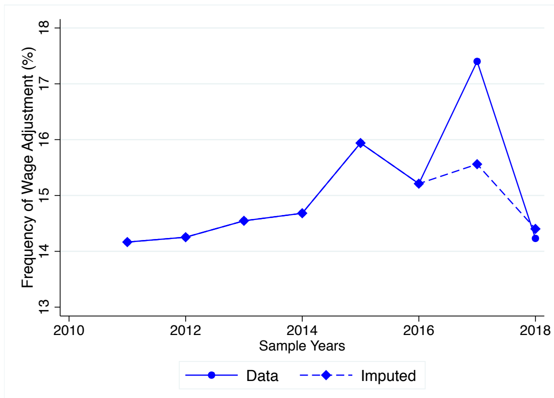
[17]The imputation was made by recoding the last two months of 2017 as the first two months of 2018 by industry. In order to rebalance the number of observations in 2017 industries' averages, the average of frequency of wage adjustments for the last two months from 2011 to 2016 was calculated by industry and imputed as the last two months in 2017. Notice that, while the imputation strategy addresses the issue in the identification strategy regarding double minimum wage adjustments in 2017, it creates a problem for the 2018 data: substituting the observed first two months in 2018 with the last two months of 2017, wage adjustments received by workers in, say, January 2018 are neglected (more likely from non-minimum wage workers). Thus, the observed and imputed values of 2018 lack from the wage adjustments of minimum and non-minimum wage workers, respectively. That is reflected in the similar values solid and dashed lines exhibit in 2018 in Figure 2. These statistics are described at great detail in Subsection 2.2.

[18]See Sigurdsson and Sigurdardottir (2016) for wages and Nakamura and Steinsson (2008) for prices.

[19]The six broad categories are (i) food-related goods, (ii) non-food goods, (iii) household-related services, (iv) education services, (v) healthcare and recreational services, and (vi) other services. The cluster of food-related goods encompasses nearly a quarter of industries.

duct inference in our benchmark model using clustered wild bootstrap-t procedure.[20] Wild bootstrap testing tends to be more conservative yielding improvements in the performance of cluster-robust methods in small samples. Following Cameron et al. (2008) and Djogbenou et al. (2019) recommendation with less than 10 clusters, we use Webb weights. The number of bootstrap replications is 999 in all regressions.

Figure 2: Frequency of Wage Adjustment.
Unweighted yearly average across industries.



Note: This figure shows the aggregate frequency of wage adjustments using data from the 70 industries in our final sample. For more on the industries in our sample, see Subsection 2.2. The aggregate yearly figures are calculated as the unweighted average of frequency of wage adjustments across industries. Industries' frequencies of wage adjustments in a given year are defined as the fraction of monthly wage changes within an industry. The solid line plots the frequency of wage adjustments as observed directly from the data; while the dashed line shows the resulting frequency once 2017 and 2018 were imputed. The imputation was made by recoding the last two months of 2017 as the first two months of 2018 by industry. In order to rebalance the number of observations in the 2017 averages, the average of frequency of wage adjustments for the last two months from 2011 to 2016 was calculated by industry and imputed as the last two months in 2017.

2.2 Data

For this paper we use highly disaggregated data for both prices and wages, as well as some aggregate data from national account statistics. In this section we first describe the price and wage datasets, we then address the measures of price and wage flexibility and its

[20]Particularly, we use the wild restricted efficient residual bootstrap developed by Davidson and MacKinnon (2010) and Roodman et al. (2019) for panel IV specifications. The clustered wild bootstrap is implemented by multiplying the residuals from the original linear model by random weights in order to construct bootstrap samples with dependent variables that are related to the independent variables by the same linear model. Inference using wild bootstrap is not new in economics. See, for instance, Busso et al. (2013) and Zimmerman (2014).

merge at industry level, finally we present the industry characteristics used as controls in our econometric framework.

Regarding prices, we use CPI microdata at product level. That is, we observe individual prices, as well as some product characteristics. Importantly, the dataset reports whether the price is categorised as sale or not.

This dataset comes from *Instituto Nacional de Estadística y Geografía* (INEGI), Mexico's National Statistical Agency, and contains the universe of prices considered in the CPI survey. A number of considerations are needed in the dataset before we can use it in our econometric framework.

First, the CPI survey takes place in Mexico twice a month (fortnightly). In order to have the same frequency of observation as our wage data, which is monthly, we opt to use the second fortnight observation of the month. Taking monthly price averages could have seen as alternative option. However, as Campbell and Eden (2014) suggest, time averages make a single price change look like two consecutive smaller changes. Thus, and without loss of generality, the second fortnight price of the month is taken as our primarily unit of observation for prices.

Second, the price dataset includes a variable classifying each individual price observation into a single product category.[21] Product categories are then grouped into 4-digit industries using the North American Industry Classification System (NAICS). It is worth mentioning that the cross-walk from product category to 4-digit industry is made publicly available by INEGI.[22] Thus, our panel's unit of observation is at industry level. The use of industry-level data has been extensively used by the nominal rigidities literature. For instance, see Dhyne et al. (2006) for a review on this literature analysing determinants of price rigidities at industry level. The analysis across industries allows us to merge the large price and wage micro-datasets in a transparent and neat way. Each dataset serves different purposes, contains different variables and the data is gathered and reported by different institutions. Although one can think of carrying out the analysis at retail and/or brand level, the variables in our

[21] Product categories are known by INEGI (in Spanish) as *Genéricos*.

[22] See INEGI (2018) for more.

datasets do not provide enough information for merging the large number of individual economic agents across datasets. Nonetheless, working at industry level is in line with much of the literature on nominal rigidities as highlighted above.

Third, few industries are dropped out from our analysis. These are industries in the non-core component of the Mexican CPI. We opt to neglect them because of three main reasons stemming from the design of the price survey. First, some prices are reported as composite prices and, thus, we are unable to disentangle what price component actually changed (e.g. holiday expenses are reported as the sum of transportation plus accommodation). Second, some prices are regulated and do not obey market conditions, particularly labor market dynamics (e.g. toll road fees). Third, the quality of some goods is not constant over time and might be reflected into prices (e.g. fresh fruit and vegetables near the end of their season). If we have had accurate price statistics for these industries (neither composite, nor regulated, nor quality driven), our identification strategy would have carried forward. As of them may be labor intensive, they would have added value to our analysis. In total, 70 out of the 283 original price categories, which translates into 16 out of the 86 industries, are neglected from the analysis.

Forth, prices in some industries are more likely to enter into sales strategies i.e. prices jumping around a reference price. Sales strategies would lead to a disproportionally high frequency of adjustment, without necessarily reflecting prices' ability to mirror their new (wage-induced) marginal cost. Fortunately, our dataset classifies prices as normal, sale, exiting sale. Thus, we are able to calculate metrics of price flexibility using all price observations, which we call "posted prices", and using sales-free prices only, which we call "normal prices".

Regarding wages, we use microdata at worker level from *Instituto Mexicano del Seguro Social* (IMSS), Mexico's Social Security Institute. That is, we observe individual workers' wages, as well as some job characteristics and demographics. Importantly for our analysis, we are able to observe the industry where the worker is employed.

This dataset contains the census of IMSS affiliated workers. A number of considerations are needed in the dataset before it is ready for our econometric framework.

First, the dataset contains the last daily wage in a given month for each worker as reported by her employer. We compare this observation month to month for calculating the frequencies of wage adjustments. A strength of our data relative to other social security or income surveys datasets is that IMSS's wages are reported as standardised base salaries. The base salary includes not only the monthly wage but pro-rata bonuses stipulated in the worker's labor contract. For instance, Mexican workers receive an end-of-year bonus in December by law. Thus, seasonal bonuses would not lead to temporal wage adjustments biasing our measures of wage flexibility.

Second, IMSS reports the industry at which the worker is employed. Importantly, IMSS uses its own industry classification system which share broad similarities to NAICS. We address the NAICS and IMSS merge in great detail below. In terms of the industry composition, the price data reports fewer industries than the wage data as it only reports final goods, while the wage data offers observations from intermediate goods (e.g. mining industry). Hence, we only consider workers in industries included in both price and wage datasets.

Third, we focus on the wages of workers who remain in the same job (job-stayers). Although few studies have considered job-switching wage changes, we opt to keep our wage rigidity measures as comparable as possible to our price analysis. That is, comparing the wage level of the same worker (item) at the same firm (retailer) relative to its wage (price) in the previous period, with presumably the same job (item) characteristics. If an individual worker has two or more jobs, he or she appears more than once in the dataset. We consider such cases as different wages as each wage (earned by the same worker) contributes to the wage flexibility of its own industry.

Forth, workers are categorised as permanent or temporal according to IMSS regulation. Our analysis only considers permanent workers. The decision not to include temporal workers is based on the fact that they are normally seasonal hires and/or upon completion of a special task (e.g. extra chores over the Christmas season). Also, wage adjustments to permanent workers is the one that matters for price determination presumably as temporal workers do not develop a job history in the firm.[23]

Having presented the features in the price and wage datasets, we move on to discuss the differences between prices' NAICS and wages' IMSS classification system.[24] Both classification systems are 4-digits and a great number of them share the same names. We identify three different cardinalities when merging industries: (i) one NAICS to one IMSS, (ii) more than one NAICS to one IMSS, and (iii) one NAICS to more than one IMSS. For the second case, price observations in multiples NAICS were pooled (unweighted) in order to calculate a single industry figure. For the last case, efforts were made to break down one NAICS code into more disaggregated codes in order to maximise the number of 1-to-1 industry relationships between NAICS and IMSS. Breaking down NAICS is possible since the price data includes product descriptions. One example are NAICS's "Beverages" and IMSS's "Beer", "Other alcoholic beverages", "Soft drinks". Using the product category variable in the price data, we disaggregate NAICS into three industries. The benefit is twofold. First, it provides a more accurate relationship between producers' wages and final prices. Second, it allows us to maximise the number of industries in our sample. As we discuss into great detail in Section 3, much of our results are explained by industry heterogeneity and not by time variation, hence the importance of disaggregating as much as possible the number of industries in our sample.

All in all, our panel of 70 industries encompasses data from 11 million of price quotes (around 60% of the CPI's expenditure weights) and 1,150 million wage observations. These industries constitute 40% of Mexico's GDP.

In order to calculate the key variables in this study, the frequencies of price and wage adjustments, we follow standard procedures in the literature (e.g. Bils and Klenow (2004); Nakamura and Steinsson (2010); Dixon and Tian (2017) for prices; and Le Bihan et al. (2012); Sigurdsson and Sigurdardottir (2016) for wages). We compute these variables in two steps. In the first step, we define a dummy variable at product (worker) level that takes the value of one if the product's price (worker's wage) changed in a given month, and zero

[23]Future work should look into whether temporal workers' wages remain flat over the contract or not; or study whether the duration of wage/employment spells is drastically different between permanent and temporal workers. This is out of the scope of the present analysis.

[24]We use the NAICS published in 2013.

otherwise. We consider the product's price (worker's wage) changed if and only if a good (worker) was observed in the current and immediate previous month and the price (wage) was not the same relative to its value in the previous month. In order to control for measurement errors, only log variation above 0.1 p.p. were taken as an actual change. Bear in mind these dummy variables are defined at product and worker level and observed at monthly frequencies. In the second step, we calculate the fraction of dummy variables reporting price and wage changes by industry per year. Equivalently, the second step can be seen as taking the yearly average by industry of the product and worker dummy variables.

Specifically, we have the following expressions for calculating our measures of flexibility:

$$FreqPriceAdj_{k,t} = \frac{\sum_{i \in k, m \in t} 1_{\text{ if } p_{i,m} \neq p_{i,m-1}}}{\sum_{i \in k, m \in t} 1_{\text{ if } p_{i,m} \text{ \& } p_{i,m-1} \text{ observed and not sales}}}$$

$$FreqPostedAdj_{k,t} = \frac{\sum_{i \in k, m \in t} 1_{\text{ if } p_{i,m} \neq p_{i,m-1}}}{\sum_{i \in k, m \in t} 1_{\text{ if } p_{i,m} \text{ \& } p_{i,m-1} \text{ observed}}}$$

$$FreqWageAdj_{k,t} = \frac{\sum_{i \in k, m \in t} 1_{\text{ if } w_{i,m} \neq w_{i,m-1}}}{\sum_{i \in k, m \in t} 1_{\text{ if } w_{i,m} \text{ \& } w_{i,m-1} \text{ observed}}}$$

where the subscript i stand for an individual product or worker, k for industries, m and t for month and year, respectively.

Hence, $FreqPriceAdj_{k,t}$, $FreqPostedAdj_{k,t}$ and $FreqWageAdj_{k,t}$ are the yearly averages of monthly frequencies of normal price, posted price and wage adjustments, respectively, for industry k in year t. The decision to have t, years, as the benchmark observation frequency in our panel is taken as some prices (e.g. services) and wages do not change every month. Little monthly variation from wages, sluggish and heterogeneous labor costs pass-through across industries, in addition to the small number of industries would lead to little power in our statistical inference.

Moreover, wages are known to be more downward rigid than prices and, while prices in some industries are also downward rigid (e.g. services' prices), price drops are more often observed in some industries (e.g. goods' prices). Negative demand shocks are a good example when this scenario might arise. Wage-setters are unable to negatively adjust their wage level, while price-setters are able to decrease their price level. In such case, we would observe an apparent disconnection between price and wage flexibility. By contrast, both wages and prices can be positively adjusted in the presence of positive demand shocks. In such case, we would observe a strong link between price and wage flexibility. Hence, in order to limit the effects on the downward asymmetries between wages and prices, a set of results studying the frequency of price and wage hikes is also analysed. Thus, we calculate:

$$FreqPriceAdj^{+}_{k,t} = \frac{\sum_{i\in k, m\in t} 1_{\text{ if } p_{i,m} > p_{i,m-1}}}{\sum_{i\in k, m\in t} 1_{\text{ if } p_{i,m} \text{ \& } p_{i,m-1} \text{ observed and not sales}}}$$

$$FreqPostedAdj^{+}_{k,t} = \frac{\sum_{i\in k, m\in t} 1_{\text{ if } p_{i,m} > p_{i,m-1}}}{\sum_{i\in k, m\in t} 1_{\text{ if } p_{i,m} \text{ \& } p_{i,m-1} \text{ observed}}}$$

$$FreqWageAdj^{+}_{k,t} = \frac{\sum_{i\in k, m\in t} 1_{\text{ if } w_{i,m} > w_{i,m-1}}}{\sum_{i\in k, m\in t} 1_{\text{ if } w_{i,m} \text{ \& } w_{i,m-1} \text{ observed}}}$$

2.3 Stylized Facts

Table 2 reports descriptive statistics by industry. More particularly, each column reports industries' averages across years for the frequency of adjustments. This is known as the within-variation in the panel data literature. For instance, column 1 is calculated as:

$$FreqPriceAdj_{k} = \frac{\sum_{t=1}^{T} FreqPriceAdj_{k,t}}{T}$$

and column 2 shows $FreqPostedAdj_{k}$. Columns 3 and 4 report industry averages using normal and posted price increases. Columns 5 and 6 provides the frequency of wage adjustments and the frequency of wage hikes only, respectively.

The frequency of price adjustment vis-à-vis the frequency of wage adjustment at industry level presented in Table 2 is noteworthy as there is no other study making this comparison in the nominal rigidities literature. Table 2 lists the complete set of industries in the panel under study. In line with the price literature (e.g. Nakamura and Steinsson (2008)) but less so with the wage literature (e.g. Sigurdsson and Sigurdardottir (2016)), there is substantial amount of heterogeneity across industries in both the frequency of price change and in the frequency of wage adjustments. On the one hand, the frequency of price changes for normal prices goes from 36% (Motor Vehicle Manufacturing) to 2% (Parking Services). The between industries' standard deviation regarding the frequency of price changes is 9.78%. On the other hand, the frequency of wage adjustment bounce between 25% (Other Household Appliances Manufacturing) and 4% (Private Households Services). The between industries' standard deviation regarding the frequency of wage adjustments is 4.62%.

Table 3 reports descriptive statistics by years. That is, it presents the yearly average across unweighted industry observations. For instance, the first row of statistics is calculated as:

$$FreqPriceAdj_t = \frac{\sum_{k=1}^{K} FreqPriceAdj_{k,t}}{K}$$

Hence, the first two rows of statistics in Table 3 provide the bloc corresponding to normal (sales-free) prices. The second set of two rows are calculated using posted prices, whereas the last two rows report yearly statistics from the wage data.

Compared to the between industry variation illustrated in Table 2, the variation across years reports considerably less variation. In fact, the standard deviation of the frequency of price adjustments and the frequency of wage changes are 1.06% and 1.12%, respectively. Thus, our results are mainly explained by industry variation and not by time variation.

It is also worth comparing the frequency of price changes and the frequency of wage adjustments in Mexico relative to other economies. Regarding posted prices, the mean is 20.43% in Mexico, while in the US is 19.3% according to Bils and Klenow (2004) and in France 19% as reported by Dixon and Le Bihan (2012). The average frequency of adjustment for normal prices in Mexico is 15.02%, nearly doubles that of the US 8.9% as calculated by Nakamura and Steinsson (2008) but similar to the UK 14% according to Dixon and Tian (2017). With respect to wages, Mexico's frequency of wage changes is 15.05%, while for the US and France is 9.9% and 14.7%, respectively, as reported by Barattieri et al. (2014) and Le Bihan et al. (2012). Thus, the Mexican economy is fairly similar to the US, France and the UK in terms of price rigidities. For wages, on the other hand, Mexico seems closer to France than to the US.

Having presented the panel's within- and between-variation, Figure 3 plots the pool of observations in our panel for the different measures of price and wage flexibility. For instance, Panel 3a depicts all k-t observations, where each diamond represents one industry in a given year, the height indicates its frequency of price adjustment and its wide reflects its frequency of wage adjustment. Panel 3b illustrates the relationship between the frequency of posted price adjustments (vertical axis) and the frequency of wage changes (horizontal axis). The second row of panels in Figure 3 follows the same idea but illustrating all observations when considering only price and wage hikes.

Few interesting stylised facts arise from Figure 3. First, in all four panels, there is a non-negligible number of observations below the 45% degree line. It implies that it is not uncommon observing years in which industries reset more frequently their wages than their prices. This stylised fact serves as evidence debunking the idea that wages are, in general, more rigid than prices. This is specially true for Panel 3c, which takes into account sales on the price data and the asymmetric downward rigidity between prices and wages. Our scatters plots show otherwise. As this study is the first merging price and wage rigidities, we could not find any reference point for other economies or if this is an idiosyncratic stylised fact for the Mexican economy.

Second, there is greater heterogeneity on the price flexibility side than in the wage flexibility as discussed when presenting Table 2. The dispersion in the vertical axis for the different panels is greater than the dispersion over the horizontal axes. Barattieri et al. (2014) hints at less dispersion on the wage flexibility side relative to the dispersion of price flexibility for the

US. However, the authors reach this conclusion by comparing the dispersion of frequencies of price changes across industries as reported in Bils and Klenow (2004) and their dispersion of the frequency of wage adjustments across different types of jobs (and not industries). We are the first to provide quantitative evidence using a consistent dimension of comparison, industries.

2.4 Industry Characteristics

For computing the industry characteristics labor costs, energy intensity and ease to adjust labor force, represented as $X_{k,t}$ in Equation 1, we use data from the KLEMS framework, provided by INEGI, and the IMSS dataset.[25] Published every year using national account statistics, KLEMS is an informative tool on the productivity of factor inputs. Due to the methodology employed in KLEMS, INEGI is able to provide an approximation on the industries' costs structures. For consistency, we use the costs structures reported at 4-digit NAICS and take them to the industry classification discussed above. Since the share of service inputs is highly labor intensive (e.g. distribution costs), we compute our proxy for the share of labor costs as the sum of labor and services shares. The industries reporting the largest and lowest share of labor costs are Private Household Services (100%) and Real State Related Activities (7%), respectively. Energy intensity is drawn directly from KLEMS' energy (E) component. The industry reporting the largest share of energy usage is Petroleum Products Manufacturing (80%). Private Household Services (0%) is the least energy intensive industry. Lastly, the ease to adjust labor force comes from the IMSS dataset. It is calculated as the standard deviation of the (log) number of workers (detrended and seasonally adjusted) by industry per year. On the one hand, Apparel Knitting Products is, on average, the industry with the most volatile labor force (1.4). On the other hand, Grain Mill Products is the one exhibiting less variation in their labor force (0.002) in our industry sample.

Finally, the share of minimum wage workers, which serves as our instrument for Equation 1, comes from the IMSS dataset. It is defined as the proportion of permanent workers

[25] KLEMS stands for capital (K), labor (L), energy (E), materials (M) and services (S).

that receive less than 1.5 times the minimum wage prevailing at the time and region for a given industry. There are two main reasons why we decide not to use the fraction of workers earning the binding minimum wage. First, only a very small fraction of workers receive the existing minimum wage. Presumably, since employers cannot report smaller wages than the existing minimum wage by law, the reservation wage across industries is above the minimum wage. Hence, the fraction of workers earning exactly one minimum wage is small and with little heterogeneity across industries. Second, workers' characteristics of those earning the minimum wage and those earning just above the minimum wage might be very similar, including the wage-setting behaviour. Adding workers earning just above the minimum wage in $FreqWageAdj^{NoMW}_{k,t}$ would weaken the relationship between the endogenous variable, $FreqWageAdj_{k,t}$, and the instrument, $\alpha^{MW}_{k,t}$, as shown in Equation 2. In other words, $FreqWageAdj^{NoMW}_{k,t}$ would get closer to $FreqWageAdj^{MW}_{k,t}$ if workers earning just above the minimum wage were included to the former. Because of the above, the 1.5 threshold gives a clear cut between the wage dynamics exhibited by minimum wage earners and non-minimum wage earners. Robustness checks (not reported) using a 1.1 threshold do not change the qualitative results whatsoever.

Table 2: Frequencies of Price and Wage Adjustments by Industry

	Prices				Wages	
	All		Hikes		All	Hikes
Industries	Normal	Posted	Normal	Posted		
	(1)	(2)	(3)	(4)	(5)	(6)
Median	13.80	17.41	9.77	11.34	15.14	12.26
Mean	15.62	20.43	10.91	12.77	15.05	12.23
Std. Dev.	9.78	13.05	6.10	7.19	4.62	3.32
Accounting, Tax Prep and Payroll Services	3.10	3.48	3.00	3.30	11.46	9.86
Activities Related to Real Estate	3.69	3.86	3.37	3.45	11.62	10.61
Alcoholic Beverage Mfg	22.05	30.75	14.30	17.91	14.65	12.09
Animal Food Mfg	32.41	40.83	21.03	24.45	15.27	12.77
Animal Slaughtering and Processing	34.69	43.62	23.51	26.83	14.95	12.31
Apparel Knitting Mills	8.93	13.26	6.17	8.11	16.81	13.70
Automotive Repair and Maintenance	5.11	5.85	4.27	4.53	8.89	7.91
Bakeries and Tortilla Mfg	16.48	23.04	11.86	14.58	11.41	9.69
Batteries and Other Electrical Equipment Mfg	18.01	23.21	12.03	13.81	19.13	14.25
Beer Mfg	18.55	23.38	13.55	15.33	19.58	13.52
Child Day Care Services	3.62	3.62	3.54	3.54	9.24	8.49
Coffee Product Mfg	25.87	35.49	16.89	20.63	11.79	9.89
Commercial and Service Ind Machinery Mfg	7.81	14.21	5.18	7.41	20.42	16.49
Confectionery Product Mfg	26.56	36.07	17.26	20.98	18.04	14.70
Converted Paper Product Mfg	29.96	38.59	18.96	22.03	16.58	13.03
Cutlery Product Mfg	13.60	18.81	10.04	12.26	17.03	13.25
Dairy Product Mfg	31.07	41.45	20.04	24.15	16.51	13.27
Death Care Services	4.80	5.52	4.20	4.41	8.91	7.96
Dry-cleaning and Laundry Services	4.93	5.39	4.43	4.60	12.01	10.82
Electric Lighting Equipment Mfg	14.01	18.33	8.81	10.88	20.00	15.69
Footwear Mfg	8.99	12.16	6.71	7.98	8.25	6.88
Fruit and Vegetable Preserving Food Mfg	29.25	39.94	18.64	22.74	16.72	13.41
Full and Limited-Service Restaurants	10.79	11.78	9.39	9.77	11.28	10.01
General Medical and Surgical Services	3.96	4.07	3.54	3.57	7.19	6.69
Glass and Glass Product Mfg	12.07	16.91	8.90	11.09	19.89	15.22
Grain Milling	34.55	43.80	21.04	24.64	14.59	12.84
Grain Processed Food	35.59	49.90	22.43	27.48	16.03	13.97
Ground Passenger Transportation	9.38	9.86	8.40	8.62	10.24	9.39
Hand tool Product Mfg	21.98	28.82	14.58	17.10	14.54	12.12
Household Appliances Mfg	20.74	33.08	14.37	19.25	22.59	17.20
Household Furniture and Kitchen Cabinet Mfg	21.35	34.02	14.78	19.69	12.11	10.29
Magnetic and Optical Media Reprod and Mfg	6.32	9.85	4.14	5.53	22.63	17.53
Medical Equipment and Supplies Mfg	10.70	13.34	7.65	8.63	22.50	17.96
Medical and Diagnostic Laboratories	4.98	6.21	4.23	4.66	11.89	9.48
Misc Musical Instruments, Toys and Sport Eq Mfg	11.81	15.97	7.99	9.63	18.24	14.69
Miscellaneous Candles and Others Mfg	13.31	17.46	9.17	11.10	11.63	8.94
Miscellaneous Jewelry and Others Mfg	9.64	13.70	6.98	8.69	10.54	8.47
Miscellaneous Stationary Mfg	13.60	16.41	9.59	10.48	23.56	17.85
Miscellaneous Wood Products Mfg	15.51	21.36	10.20	12.48	10.60	9.14
Motion Picture and Video Industries	9.86	10.69	8.71	9.04	13.03	10.76
Motor Vehicle Mfg	35.91	38.67	26.32	26.76	23.97	18.56
Motor Vehicle Parts Mfg	12.86	14.22	9.74	10.06	23.49	17.91
Newspaper, Periodical and Book Publishers	5.63	5.90	4.60	4.67	11.08	9.21
Nightclubs, Pubs and Canteens	4.15	4.34	3.59	3.66	13.91	11.29
Non-alcoholic Beverage Mfg	17.51	24.14	12.64	15.47	16.98	13.98
Offices of Dentists	4.09	4.54	3.56	3.75	10.35	8.34
Oilseed Milling	35.25	45.66	21.44	25.38	19.00	14.49
Other Amusement and Recreation Industries	4.46	4.89	3.72	3.86	15.01	11.93
Other Chemical Product and Preparation Mfg	11.04	12.75	7.77	8.31	19.95	16.86
Other Electrical Equipment Mfg	17.46	19.98	13.57	14.43	18.68	15.42
Other Food Mfg	21.30	30.49	14.45	18.17	10.88	9.05
Other Furniture Related Product Mfg	19.01	30.38	13.26	17.65	20.21	15.92
Other Household Appliances Mfg	14.12	22.85	9.82	13.64	24.54	18.98
Other Leather and Allied Product Mfg	9.66	14.72	6.59	8.82	15.33	12.11
Other Transportation Equipment Mfg	14.41	20.10	10.48	12.41	15.34	11.87
Parking Related Services	1.88	1.87	1.71	1.70	10.45	8.92
Perfumes and Cosmetics Mfg	17.96	25.69	11.66	14.93	15.54	12.70
Personal Care Services	3.22	3.66	2.91	3.07	6.02	5.87
Personal and Household Goods Repair	9.58	13.45	6.72	8.25	8.54	7.26
Pesticide and Fertilizer Mfg	30.84	38.86	19.19	21.91	12.48	10.11
Petroleum Products Mfg	14.42	17.38	10.58	11.60	14.47	12.22
Pharmaceutical and Medicine Mfg	26.49	29.81	18.52	19.34	19.00	15.23
Plastics Product Mfg	10.47	14.19	7.41	8.94	16.95	13.41
Private Households Services	2.97	2.98	2.72	2.72	4.22	4.08
Rubber Product Mfg	19.38	26.20	13.58	15.71	14.59	11.44
Seafood Product Preparation and Packaging	28.02	38.24	17.58	21.56	13.22	10.75
Soap and Cleaning Compound Mfg	29.39	39.01	18.23	21.65	16.81	14.19
Textile Furnishings Mills	9.72	14.51	6.88	9.03	15.53	12.53
Tobacco Mfg	15.06	15.08	14.45	14.45	19.49	15.92
Water Supply Services	17.65	17.66	16.80	16.81	15.39	12.65

Note: This table lists the complete set of industries in our panel (70). Columns report industries' frequencies of adjustment averaged across time. Averages are calculated using data from 2011 to 2018. Column 1 to column 6 present the frequency of normal price adjustments, posted price changes, normal price hikes, posted price increases, wage adjustments and wage increases, respectively. Median, mean and standard deviation are unweighted moments across industries.

Table 3: Frequencies of Price and Wage Adjustments by Year

Frequency of Adjustments	2011	2012	2013	2014	2015	2016	2017	2018	Median	Mean	Std. Dev.
Normal Prices											
All Changes	16.29	15.01	14.01	15.27	14.62	15.84	16.96	16.93	15.56	15.62	1.076
Hikes Only	11.33	10.72	9.395	10.64	10.11	11.16	12.42	11.55	10.94	10.91	0.926
Posted Prices											
All Changes	20.79	19.78	19.19	20.63	19.78	20.82	21.75	20.67	20.65	20.43	0.801
Hikes Only	12.95	12.55	11.52	12.74	12.20	12.99	14.11	13.08	12.85	12.77	0.748
Wages											
All Changes	14.16	14.25	14.54	14.68	15.93	15.21	17.40	14.23	14.61	15.05	1.122
Hikes Only	11.35	11.43	11.87	11.84	13.09	12.29	14.63	11.33	11.86	12.23	1.133

Note: This table reports descriptive statistics on the frequencies of adjustments by years. It presents years' averages across unweighted industry observations. That is, for a given year t, the average value of the frequency of adjustment across industries in year t is calculated. There are 70 industries in our sample. The first two rows of statistics provide the bloc corresponding to normal prices. The second set of two rows are calculated using posted prices, whereas the last two rows report wage statistics. Median, mean and standard deviation are unweighted moments across years.

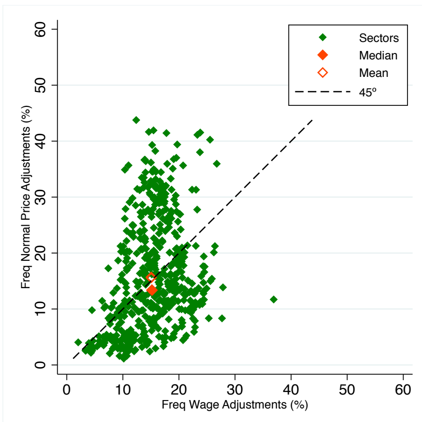
3 Results

Table 4 reports estimates of regressing the frequency of normal price adjustments on the frequency of wage changes plus industry and year fixed effects. The first three columns present standard OLS estimates, whereas the latter three offer the results when the frequency of wage adjustment is instrumented with the share of minimum wage workers. Bear in mind the frequency of normal price adjustments is calculated filtering out sales prices.

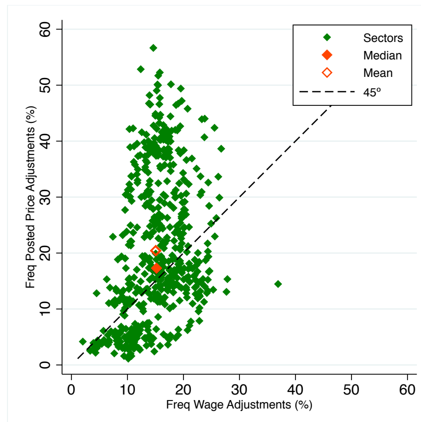
Within each of the OLS and IV set of results, Table 4 shows the coefficients using three different time samples following the arguments presented in Subsection 2.1.[26] The coefficient in column 1 is calculated using years when only one minimum wage adjustment was observed. Historically, in Mexico there is normally only one minimum wage adjustment in the year. Consequently, the time restriction used in column 1 is under the title "Standard". The coefficient in column 2, titled "Data", is obtained using observations from 2013 until

[26] Using years with more than one minimum wage adjustment might lead both terms on the right hand side of Equation 2 to cancel out and resulting in a non-relevant instrument. See Subsection 2.1 for more.

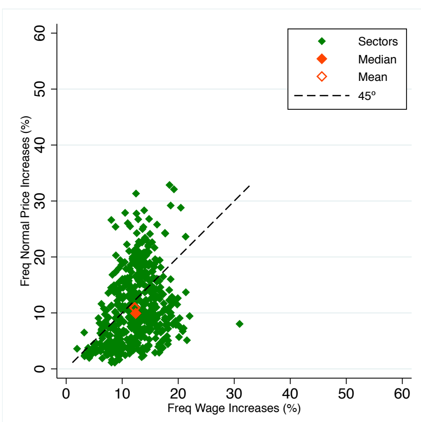
Figure 3: Frequencies of Adjustments.
One observation per industry per year.



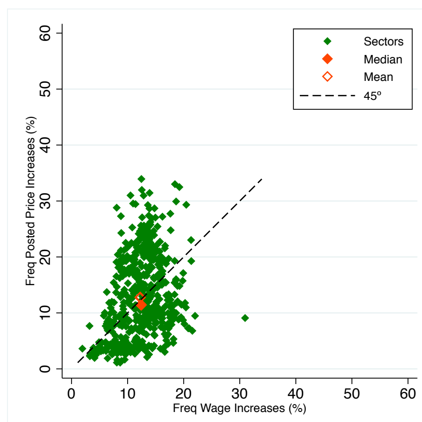
(a) Normal Prices and Wages. All Changes.



(b) Posted Prices and Wages. All Changes.



(c) Normal Prices and Wages. Hikes Only.



(d) Posted Prices and Wages. Hikes Only.

Note: The four panels plot the pool of observations in our panel for the different measures of price and wage flexibility. In all panels, each diamond represents one observation per industry per year. The height indicates the frequency of price adjustment and the width reflects the frequency of wage adjustment per industry per year. Panel 3a depicts the relationship between the frequency of price adjustments (vertical axis) and the frequency of wage changes (horizontal axis). Panel 3b illustrates the frequency of posted price adjustments and the frequency of wage changes. Panel 3c compares the frequency of price increases and the frequency of wage hikes. Panel 3d presents the frequency of posted price increases and the frequency of wage hikes.

2018. Bear in mind that by using the full time span, the years with more than one minimum wage adjustment (2015 and 2017) or no adjustment (2018) are included in the sample. As discussed in great detail in Section 2, attempts were made to impute the 2018 observations using data from late 2017. Column 3, under the title "Imputed", reports the calculated coefficient using the 2017 and 2018 imputed data. The same time specifications are repeated in columns 4 to 6 but calculated via IV estimation.

Using standard years with one minimum wage adjustment, OLS estimates in Table 4 show a positive point estimate of 0.359. This result suggests a positive relationship between price and wage flexibility. Note, however, point estimates are statistically insignificant. OLS estimates including the whole time span as observed from the data are considerable lower and even with a negative sign, -0.011. This coefficient is not only statistically insignificant but also less precise than the coefficient using only standard years as shown by their p-value. The third column in Table 4 tells a similar story than column 2 with a coefficient closer to zero, -0.007. Hence, imputing seems to have little payoff in order to use more recent data.

In order to address any potential bias in our OLS estimates arising from endogeneity, we look into the panel IV approach for critically studying whether wage flexibility causes price flexibility. Columns 4 to 6 reporting the panel IV results assert the story told in columns 1 to 3 using an OLS framework. The different order of magnitudes confirm our endogeneity concerns presented in Section 2. We come back to this issue after discussing the IV results.

Firstly, the coefficient of our variable of interest, the frequency of wage adjustment, is positive and statistically significant when years with multiple minimum wage revisions are excluded from the model (column 4). This is a key result in our research. The coefficient can be interpreted as, for a 1 p.p. increase in the frequency of wage adjustments, it increases price flexibility, in the form of the frequency of price adjustments, by 1.223 p.p. The first stage in this specification also exhibits a statistically significant and negative sign as expected from Equation 2. The F-statistic, around 30, provides some support that we do not have a problem of weak identification between the instrument and the endogenous regressor. Moving into estimates without imputations in 2017 and 2018, column 5, the point estimate of 0.812 is smaller and less precise than employing standard years only. Nonetheless, it contrasts with its OLS counterpart from column 2 by remaining above zero. Regarding column 6, imputing 2017 and 2018 observations, the coefficient close to unity, 1.071, but statistically insignificant. Also, note that the first stage coefficients in column 5 and column 6 are smaller than in column 4, and thus, less precise second stages. We attribute this effect to the years with atypical minimum wage adjustment policies in such years which dampens our instrument's identification strategy.

The differences between OLS and IV estimates in Table 4 are indicative of the potential endogeneity problems discussed in Section 2. However, the downward bias is somewhat counterintuitive to the obvious omitted variable candidate for which our regression cannot control for: a productivity shock. After a productivity shock, more frequent wage revisions are expected as the wage level rises. Likewise for prices due to the greater demand for goods and services. Thus, a productivity shock would affect both price and wage frequencies of adjustments resulting in an upward biased OLS estimation.

One way to reconcile the downward bias found in Table 4 is to think on industries that, on the one hand, exhibit great price flexibility; and, on the other hand, wage-setters abstracting from such fluctuations by setting up labor contracts avoiding frequent wage fluctuations. Importantly, due to labor market regulations, unions/households would be particularly averse to wage decreases. Thus, reverse causality might be particularly acute in sectors with little downward price rigidity but great downward wage rigidity (e.g. prices in the goods market). In other words, greater price flexibility resulting in greater wage rigidities. Reverse causality in this case would downward bias standard OLS results.

Secondly, Table 5 contrasts the results using price and wage increases only and considering normal prices (i.e. including sales). As highlighted in Section 2, comparing different specifications on how the frequencies of price adjustments are calculated, particularly when taking a stand on the presence of sales and sign of price changes, limits the possibility of a spurious price and wage relationship. This relation can arise due to industries often engaged in sales strategies and/or the asymmetries in downward adjustment that prices and wages exhibit.[27]

The first four columns in Table 5 report estimates using standard OLS, while the latter four show the coefficients when the frequency of wage adjustment is instrumented using our proposed instrument. It is important to highlight that estimates reported in Table 5 use the years with only one minimum wage adjustment. These are the same years used under the header "Standard" in Table 4. The estimates in Table 5 remain robust to the change on the way the frequencies of adjustments are calculated. All OLS estimates stay close to the 0.3 p.p value but statistically insignificant. Column 1 and column 2 show the coefficients when considering all prices changes (regardless their sign of adjustment) for normal and posted prices, respectively. These are 0.359 p.p. and 0.358 p.p. Column 3 and column 4 report the results using only price and wage increases for normal and posted prices, 0.311 p.p. and 0.330 p.p., respectively.

IV estimates in Table 5 are all positive and statistically significant. Column 6 shows that the frequency of posted price adjustments increases by 1.219 p.p. after a 1 p.p. increase in the frequency of wage changes. The same goes when centering the attention on positive adjustments. An increase of 1 p.p. in the frequency of wage hikes results in a 1.2 p.p. rise in the frequency of price increases as reported in column 7 and column 8.

In the Appendix, we provide numerous robustness checks with different specifications. First, Table 9 and Table 10 consider all years available in the datasets back to 2011. The results from these Tables align with those in Table 4 and Table 5, respectively, despite the methodological changes in the price survey prior 2013.[28] Second, we complement our external instrument with an internal instrument drawn from lagged values of the frequency of the wage adjustments. The short panel at hand was in important determinant for pursuing an

[27]Nakamura and Steinsson (2010) documents that statistics on the frequency of price adjustments are sensitive to the sales treatment assumptions taken by the researcher. Different assumptions can lead to very different conclusions. Regarding the asymmetries in downward adjustment, wages exhibit great downward rigidities (see, among others, Le Bihan et al. (2012)); whereas downward rigidity for prices is heterogeneous depending on the type of good or service (Álvarez et al. (2006) document that price decreases are not rare, except in service prices).

[28]The 2011-2012 considers the same industries but few price categories within industries and sample sizes are not entirely the same relative to the 2013-2018 dataset.

external instrument approach. Nonetheless, Table 11 and Table 12 in the Appendix report our results hold when two instruments are used with data from 2011 and 2013 onwards, respectively. The positive impact of wages on prices is positive and statistically significant when all changes are considered.[29]

Moving into the role of industry characteristics explaining price flexibility, studies like Peneva (2011) and Álvarez et al. (2006) have found and inverse relationship between labor intensity in the cost function and the frequency of price adjustment. The intuition is based on the fact that, as wages are more rigid than prices, the more prices depend on labor costs, the more rigid prices are. Moreover, Álvarez and Hernando (2005) document that the share of energy-related inputs is positively related to the degree of price flexibility. Our framework allows us to test these findings for the Mexican economy.

Other margin in which prices and labor costs might be related is through the employment level. In other words, the number of workers and how easy it is for certain industries to adjust their labor force. If such case, a more muted frequency of wage adjustment might be observed and therefore no reflection onto prices. Industries might experience different degrees of easiness to adjust their labor costs due to, for instance, degree of unionised workers (presumably increasing the cost of laying off workers) or depending how much industries rely on their human capital (substitution of low skill workers might decrease the costs of adjusting the labor force). This margin of adjustment is yet to be explored in the context of price flexibility to the best of our knowledge. As described in the data section, we first detrend and seasonally adjust the monthly series of number of workers by industry. Then, the standard deviation of monthly observations is calculated per year by industry. We end up with the same frequency of observation as in our panel: one observation per industry per year. This variable is interpreted as the ability industries have to adjust their labor force. Intuitively, the greater volatility an industry exhibits in its employment level, the less related prices are to wages as labor costs might not necessarily increase at times of wage revisions. Thus, we expect a negative relationship between this covariate and the frequency of price adjustment.

[29] For completeness, we provide evidence when the lagged frequency of wage adjustment acts as the only instrument. Although positive, estimates are less precise and statistically insignificant. See Table 13 and Table 14.

Table 6 reports our estimates from Equation 1, the regression adding as exogenous regressors labor share, energy intensity and our proxy for the ability industries have to adjust their labor force. Note, however, costs' structures across industries are unlikely to exhibit a lot of variation in a short period of time as our panel encompasses. Nonetheless, our analysis allows assessing if previous results in the literature using these regressors hold when the frequency of wage adjustment is included in the regression. As mentioned in the Introduction, one of the main conclusions from the Inflation Persistent Network was that wages are key determinants of price adjustments.

Findings from Table 6 confirm the important role wage flexibility plays explaining price flexibility. When controlling for endogeneity using an IV, the frequency of wage adjustment has a positive effect on price flexibility. See column 5 to column 8 in Table 6. The magnitudes of these coefficients are around 1.4 and statistically significant. They are only slightly greater than those reported in Table 4 and Table 5.

One interesting result arises from Table 6. Focusing on the OLS estimates, column 1 to column 4, labor share exhibits a negative relationship with respect to price flexibility. This result is consistent with studies like Peneva (2011), Vermeulen et al. (2012) and Álvarez et al. (2006) who documented the inverse relationship between the frequency of price adjustment and labor share for the US and some EU economies. The authors intuition is that, as wages are more rigid than prices, the greater dependence of prices on wages (greater labor share) the more rigid prices are. The aforementioned authors claim a strong and robust negative relationship between labor share and the frequency of price adjustments. However, when the frequency of wage adjustments is included in an OLS specification, as we did from column 1 to column 4 in Table 6, the labor share coefficient remains negative but it is not statistically significant. In order verify if our datasets support Peneva (2011), Vermeulen et al. (2012) and Álvarez et al. (2006) findings, specially when the frequency of wage adjustment is omitted from the regression, we run again an OLS regression without this regressor. Table 7 reports the results from this regression. Strikingly, when the frequency of wage adjustment is omitted in the OLS regression, labor share is negative and statistically significant, in line with the literature. Thus, our findings suggest that omitting a measure of wage flexibility can lead to different conclusions when assessing the determinants of price flexibility.[30] Coming back to Table 6, labor share in the IV specification, column 5 to column 8, becomes positive but remains statistically insignificant. The sign flip is not at odds with the intuition posed by Peneva (2011), Vermeulen et al. (2012) and Álvarez et al. (2006): the more prices depend on wages (greater labor share), the more wage flexibility affects price flexibly.

The link between the frequency of price and wage adjustment has been previously mentioned in the literature. Indeed, Klenow et al. (2010) acknowledges this relationship as one of the ten stylised facts in micro-price research. However, the evidence has been so far shown indirectly via labor share. Our study is the first to shed light between the link of the frequencies of price and wage adjustments. Thus, one can interpret our results as labor share influencing price flexibility only through wage adjustments.

With respect to energy intensity, Table 6 shows a negative and statistically insignificant coefficient. That is the case regardless using posted or normal prices, all changes or only positive ones, or OLS or IV estimation. The negative coefficient for this covariate contrasts with Álvarez and Hernando (2005) finding a positive relationship between the frequency of price adjustment and how intensive the industry is in terms of energy (fuel) consumption. We interpret the opposite sign as idiosyncratic of the Mexican economy: throughout the years in our panel, most energy-related input prices were regulated by the government and not market driven (as in most advance economies where these inputs exhibit greater volatility).[31]

Finally, our proxy capturing how easy it is for certain industries to adjust their labor force reports a positive coefficient. The positive relationship is at odds with our hypothesis that the more volatile their labor force is, the less price flexibility would be a reflection of wage flexi-

[30] In the Appendix, Table 15 reports results from a more parsimonious specification than Table 6. That is, using the frequency of wage adjustments and the share of labor costs as the only explanatory variables.

[31] A number of different price setting rules for gasoline, gas and electricity prevailed over our sample years. Most of these rules aimed at smoothing price variations while providing forward guidance on prices (e.g. releasing price schedules nearly a year in advance). Price setting rules were set by monopolistic state-owned companies on oil, gas and electricity, along with the fiscal authority. Hence, price flexibility on energy prices did not reflect market conditions as it does in most developed economies where a number of firms compete setting prices. In fact, because of this reason energy related industries were neglected from the analysis, as highlighted in Subsection 2.2.

bility. The positive sign implies that, industries exhibiting more volatile labor force are those changing more frequently their prices. This result might be explained by some industries which, in the presence of a negative shock for instance, they adjust both prices and labor force (to adjust production). Firm level data is required in order to shed further light on whether labor force adjustment uncovers the disconnection between workers' wages and goods' prices.

Table 4: Frequency of normal price adjustments on the frequency of wage adjustments

	OLS			IV		
Sample	Standard	Data	Imputed	Standard	Data	Imputed
years	13,14,16	2013-2018	2013-2018	13,14,16	2013-2018	2013-2018
	(1)	(2)	(3)	(4)	(5)	(6)
Second Stage						
Freq of Wage Adj	0.359	-0.011	-0.007	1.223*	0.812	1.071
	[0.112]	[0.825]	[0.891]	[0.069]	[0.643]	[0.639]
First Stage						
MW Share				-0.141**	-0.099*	-0.081
				[0.034]	[0.093]	[0.124]
Observations	210	420	420	210	420	420
Number of Industries	70	70	70	70	70	70
Number of Clusters	6	6	6	6	6	6
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Partial R2				0.076	0.031	0.026
Robust F				31.013	30.637	12.422

Note: This table reports estimates from a regression of the frequency of normal price adjustments on the frequency of wage changes plus industry and year fixed effects. Normal prices' metrics are those where sales were filtered out. The first set of three columns adjust an OLS model for three different sample years. Column 1, titled "Standard", uses years when there was only one minimum wage adjustment. Column 2, titled "Data", uses all observations as directly observed from the data. Column 3, titled "Imputed", uses all observations but the 2017 and 2018 observations for all industries were adjusted. This adjustment came in the form of imputing 2018 with data from the second minimum wage adjustment in 2017; and the 2017 data only reflects wage adjustments from the first minimum wage change in that year. Column 4 to column 6 follow the same restrictions in terms of sample years but using a panel IV framework. Our variable of interest, the frequency of wage adjustment, is instrumented with the share of minimum wage workers. Figures in squared brackets are p-values calculated with wild bootstrapped standard errors clustered at 6 broad industry categories.

Table 5: Different frequencies of price adjustments on the frequency of wage adjustments

	OLS				IV			
	All Changes		Positive Changes		All Changes		Positive Changes	
	Normal	Posted	Normal	Posted	Normal	Posted	Normal	Posted
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Second Stage								
Freq of Wage Change	0.359	0.358	0.311	0.330	1.223*	1.219*	1.205*	1.205*
	[0.112]	[0.121]	[0.144]	[0.180]	[0.069]	[0.090]	[0.069]	[0.077]
First Stage								
MW Share					-0.141**	-0.141**	-0.130*	-0.130*
					[0.034]	[0.034]	[0.057]	[0.057]
Observations	210	210	210	210	210	210	210	210
Number of Industries	70	70	70	70	70	70	70	70
Number of Clusters	6	6	6	6	6	6	6	6
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Partial R2					0.076	0.076	0.070	0.070
Robust F					31.013	31.013	73.415	73.415

Note: This table reports the regression results of the frequency of adjustment of different price specifications on the frequency of wage changes plus industry and year fixed effects. The price specifications are normal prices (sales are filtered out), posted prices (include sales) and price hikes (considering only positive price changes). When the dependent variable is the frequency of price increases, the frequency of wage increases is used in the right hand side of the equation. All columns use data from 2013, 2014, 2016. In these years there was only one minimum wage adjustment. The first set of four columns adjust an OLS model. The latter set of four columns use a panel IV framework. The frequency of wage adjustment or the frequency of wage increases, depending the case, are instrumented with the share of minimum wage workers. Figures in squared brackets are p-values calculated with wild bootstrapped standard errors clustered at 6 broad industry categories.

Table 6: Frequencies of price adjustments on the frequency of wage adjustments and industry characteristics

	OLS				IV			
	All Changes		Positive Changes		All Changes		Positive Changes	
	Normal	Posted	Normal	Posted	Normal	Posted	Normal	Posted
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Second Stage								
Freq of Wage Change	0.357	0.319	0.317	0.305	1.427*	1.387*	1.414*	1.346*
	[0.121]	[0.155]	[0.156]	[0.216]	[0.077]	[0.091]	[0.080]	[0.080]
Share of Labor Costs	-0.087	-0.220	-0.020	-0.113	0.348	0.215	0.327	0.217
	[0.586]	[0.213]	[0.883]	[0.614]	[0.139]	[0.147]	[0.151]	[0.173]
Energy Intensity	-0.074*	-0.055	-0.019	0.025	-0.193	-0.174	-0.116	-0.066
	[0.074]	[0.342]	[0.584]	[0.918]	[0.165]	[0.269]	[0.287]	[0.230]
Lab Force Adj Ease	0.385	0.471	0.536	0.259	0.893	0.978	1.090	0.785
	[0.748]	[0.706]	[0.800]	[0.765]	[0.574]	[0.509]	[0.138]	[0.297]
First Stage								
MW Share					-0.119**	-0.119**	-0.112*	-0.112*
					[0.042]	[0.042]	[0.066]	[0.066]
Share of Labor Costs					-0.373***	-0.373***	-0.285**	-0.285**
					[0.002]	[0.002]	[0.027]	[0.027]
Energy Intensity					0.104	0.104	0.081	0.081
					[0.605]	[0.605]	[0.684]	[0.684]
Lab Force Adj Ease					-0.348	-0.348	-0.385	-0.385
					[0.335]	[0.335]	[0.232]	[0.232]
Observations	210	210	210	210	210	210	210	210
Industries	70	70	70	70	70	70	70	70
Clusters	6	6	6	6	6	6	6	6
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Partial R2					0.061	0.061	0.056	0.056
Robust F					34.304	34.304	76.754	76.754

Note: This table reports the regression results of the frequency of adjustment of different price specifications on the frequency of wage changes plus industry of characteristics and industry and year fixed effects. The price specifications are normal prices (sales are filtered out), posted prices (include sales) and price hikes (considering only positive price changes). When the dependent variable is the frequency of price increases, the frequency of wage increases is used in the right hand side of the equation. All columns use data from 2013, 2014, 2016. In these years there was only one minimum wage adjustment. The first set of four columns adjust an OLS model. The latter set of four columns use a panel IV framework. The frequency of wage adjustment or the frequency of wage increases, depending the case, are instrumented with the share of minimum wage workers. Figures in squared brackets are p-values calculated with wild bootstrapped standard errors clustered at 6 broad industry categories.

Table 7: Omitting the frequency of wage adjustment

	OLS			
	All Changes		Positive Changes	
	Normal	Posted	Normal	Posted
	(1)	(2)	(3)	(4)
Share of Labor Costs	-0.232**	-0.350	-0.121**	-0.210**
	[0.049]	[0.158]	[0.028]	[0.037]
Energy Intensity	-0.034	-0.019	0.009	0.052
	[0.519]	[0.621]	[0.835]	[0.768]
Lab Force Adj Ease	0.215	0.319	0.375	0.105
	[0.845]	[0.784]	[0.822]	[0.860]
Observations	210	210	210	210
Industries	70	70	70	70
Clusters	6	6	6	6
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes

Note: This table reports the regression results of the frequency of adjustment of different price specifications on industry of characteristics plus industry and year fixed effects. It omits the main variable of interest, the frequency of wage changes. The idea is to analyse whether our data supports Peneva (2011) and Álvarez et al. (2006) findings regarding the inverse relationship between price flexibility and the share of labor costs. To that end, we use an OLS framework consistent with their work. Please refer to Table 6 for results including the frequency of wage adjustment in the regression. Figures in squared brackets are p-values calculated with wild bootstrapped standard errors clustered at 6 broad industry categories.

Table 8 provides estimates from a cross-sectional framework. The cross-section of industries comes from averaging out their time dimension. Importantly, the average per industry is calculated using only the years with one minimum wage increase in our sample. That is, 2013, 2014 and 2016. Thus, Table 8 is the cross-section equivalent of Table 5 but only using the between variation. As mentioned in Section 2, the cross sectional estimates offers a consistent comparison of this study to a strand on the price rigidities literature. Furthermore, it allows assessing industry characteristics which, unfortunately, are time-invariant.

Coefficients reported in Table 8 offer the same qualitative results as our panel framework, despite adding more exogenous variables. First, the frequency of wage adjustments is a positive driver of price flexibility. Industries that tend to adjust their wages more often, are those resetting their prices more frequently. Second, labor costs is inversely related to the frequency of price changes but becomes statistically insignificant when we move to the IV framework controlling for potential two-way bias. Third, not accounting for the degree of informality might bias the effects of wage flexibility on price flexibility. Although industry fixed effects control for this feature in the panel, the results in Table 8 suggest it plays very little role in explaining the frequency of price flexibility. Forth, energy intensity is positive but statistically insignificant as in the previous econometric model. Energy prices were regulated by the government over the years of observation, exhibiting little volatility. Finally, we add two covariates which reflect the openness to imports of some Mexican industries. These are import shares and the exchange rate pass-through.[32] Despite the fact that they are related, the former controls on how little prices might depend on domestic (labor) costs as the import share increases; the latter is seen as the ability or inability to pass-through costs (e.g. due to competition). Both covariates, imports intensity and exchange rate pass-through, exhibit moderate effects on the frequency of price adjustment- negatively and positively, respectively. In the Appendix, we provide cross-sectional estimates where the averages by industry are calculated all years in our sample. The results remain robust to this variation in our sample. Importantly, an increase in the frequency of wage adjustment causes an increase in the frequency of price changes.[33]

The cross-sectional exercise sheds further light on the importance of the frequency of wage adjustments explaining the frequency of price changes. Instead of using industry fixed effects, the cross-section confirms that industry heterogeneity drives much of the results, consistent with the literature studying price rigidities.

[32]Exchange-rate pass-through estimates are borrowed from Kochen and Sámano (2016).

[33]See Appendix, Table 16

Table 8: Estimates from a Cross-Section of Industries

	OLS				IV			
	All Changes		Positive Changes		All Changes		Positive Changes	
	Normal	Posted	Normal	Posted	Normal	Posted	Normal	Posted
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Freq of Wage Change	0.371	0.431	0.398**	0.419*	1.329*	1.628*	1.297*	1.461*
	[0.253]	[0.290]	[0.012]	[0.080]	[0.073]	[0.075]	[0.061]	[0.076]
Labor Costs	-0.264*	-0.368*	-0.158*	-0.199*	-0.171	-0.251	-0.093	-0.124
	[0.075]	[0.085]	[0.075]	[0.068]	[0.227]	[0.191]	[0.329]	[0.294]
Labor Force Adj Ease	-0.044	-0.049	-0.029	-0.029	-0.075	-0.088	-0.049	-0.053
	[0.370]	[0.476]	[0.316]	[0.391]	[0.314]	[0.305]	[0.277]	[0.284]
Informality Share	0.027	0.056	-0.000	0.012	0.093	0.139	0.041	0.059
	[0.788]	[0.713]	[0.998]	[0.878]	[0.425]	[0.355]	[0.464]	[0.415]
Energy Intensity	0.031	0.006	0.018	0.006	0.089	0.078	0.047	0.040
	[0.613]	[0.940]	[0.646]	[0.881]	[0.291]	[0.355]	[0.290]	[0.392]
Imports Share	-0.030	0.025	-0.060	-0.039	-0.103	-0.067	-0.116*	-0.103*
	[0.697]	[0.807]	[0.325]	[0.517]	[0.377]	[0.567]	[0.057]	[0.083]
FX Pass-through	0.392**	0.620**	0.204**	0.300**	0.293	0.496*	0.133	0.218
	[0.024]	[0.021]	[0.041]	[0.022]	[0.193]	[0.060]	[0.350]	[0.138]
Industries	70	70	70	70	70	70	70	70
Clusters	6	6	6	6	6	6	6	6
Partial R2	0.328	0.351	0.322	0.349	0.556	0.556	0.475	0.475
Robust F	10.134	9.417	12.277	10.146	29.320	29.320	20.180	20.180

Note: This table reports the regression results from a cross-section of industries. Industry observations come from averaging out their time dimension. The average per industry is calculated using only the years with one minimum wage increase in our sample. That is, 2013, 2014 and 2016. The cross sectional estimates allow us assessing time-invariant industry characteristics. Figures in squared brackets are p-values calculated with wild bootstrapped standard errors clustered at 6 broad industry categories.

4 Conclusions

This paper analyses whether the frequency of price changes is affected by the frequency of wage adjustments. We study the connexion using an instrumental variable panel data approach at the industry level. The results from this paper indicate that industries adjusting their wages more often are those resetting their prices more frequently. Hence, there is a positive effect of wage flexibility on price flexibility. Such finding is true not only when sales prices are filtered out, but when we analyse posted prices including sales. Also, since wages are known to be more downward rigid than prices, our quantitative and qualitative results hold when analysing the effects of frequency of wage increases on the frequency of price hikes only. When our variable of interest, the frequency of wage adjustments, is included in the econometric framework to analyze the determinants of the frequency of price adjustments, the share of labor costs becomes less relevant in explaining the heterogeneous price flexibility across industries.

Price and wage rigidities are key determinants in the predictions drawn from New Keynesian models. Yet, the evidence regarding the relationship between these two sources of nominal rigidities is limited, despite their obvious relationship via marginal costs. Thus, our study contributes to fill this gap in the literature by showing that more frequent wage revisions result in more frequent price adjustments. Consequently, our findings contribute to the price rigidities' literature by adding into the debate the non-negligible role wage flexibility plays in price-setting. The interaction between these two frictions is non-trivial. As the literature on DSGE modelling suggests, taking seriously the heterogeneous degrees of price and wage flexibility as observed in the microdata alters the predictions generated by macroeconomic models.

Future work with firm-level data could shed light on the mechanisms price-setters care about when determining how frequently they adjust their prices in response to firm-specific wage-setting policies.

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Appendix

Panel IV: Additional Regressions

Table 9: Estimates by OLS and Panel IV with Extended Panel

	OLS			IV		
Sample	Standard	Data	Imputed	Standard	Data	Imputed
years	11-14,16	2011-2018	2011-2018	11-14,16	2011-2018	2011-2018
	(1)	(2)	(3)	(4)	(5)	(6)
Second Stage						
Freq of Wage Adj	0.217**	-0.003	0.002	0.388*	0.308	0.386
	[0.040]	[0.955]	[0.958]	[0.068]	[0.685]	[0.649]
First Stage						
MW Share				-0.086*	-0.093**	-0.083**
				[0.056]	[0.037]	[0.043]
Observations	350	560	560	350	560	560
Number of Industries	70	70	70	70	70	70
Number of Clusters	6	6	6	6	6	6
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Partial R2				0.035	0.034	0.032
Robust F				14.297	29.181	17.005

Note: This table reports estimates from a regression of the frequency of normal price adjustments on the frequency of wage changes plus industry and year fixed effects. Normal prices' metrics are those where sales were filtered out. The first set of three columns adjust an OLS model for three different sample years. Column 1, titled "Standard", uses years when there was only one minimum wage adjustment. That is, 2011-2014 and 2016. Column 2, titled "Data", uses all observations as directly observed from the data. Column 3, titled "Imputed", uses all observations but the 2017 and 2018 observations for all industries were adjusted. This adjustment came in the form of imputing 2018 with data from the second minimum wage adjustment in 2017; and the 2017 data only reflects wage adjustments from the first minimum wage change in that year. Column 4 to column 6 follow the same restrictions in terms of sample years but using a panel IV framework. Our variable of interest, the frequency of wage adjustment, is instrumented with the share of minimum wage workers. Figures in squared brackets are p-values calculated with wild bootstrapped standard errors clustered at 6 broad industry categories.

Table 10: Different Measures of Freq of Price Adj. Extended Panel

	OLS				IV			
	All Changes		Positive Changes		All Changes		Positive Changes	
	Normal	Posted	Normal	Posted	Normal	Posted	Normal	Posted
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Second Stage								
Freq of Wage Change	0.217**	0.279	0.131	0.152	0.388*	0.435*	0.568	0.629
	[0.040]	[0.139]	[0.194]	[0.201]	[0.068]	[0.099]	[0.417]	[0.257]
First Stage								
MW Share					-0.086*	-0.086*	-0.052*	-0.052*
					[0.056]	[0.056]	[0.097]	[0.097]
Observations	350	350	350	350	350	350	350	350
Number of Industries	70	70	70	70	70	70	70	70
Number of Clusters	6	6	6	6	6	6	6	6
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Partial R2					0.035	0.035	0.016	0.016
Robust F					14.297	14.297	9.057	9.057

Note: This table reports the regression results of the frequency of adjustment of different price specifications on the frequency of wage changes plus industry and year fixed effects. The price specifications are normal prices (sales are filtered out), posted prices (include sales) and price hikes (considering only positive price changes). When the dependent variable is the frequency of price increases, the frequency of wage increases is used in the right hand side of the equation. All columns use data from 2011 to 2014 and 2016. In these years there was only one minimum wage adjustment. The first set of four columns adjust an OLS model. The latter set of four columns use a panel IV framework. The frequency of wage adjustment or the frequency of wage increases, depending the case, are instrumented with the share of minimum wage workers. Figures in squared brackets are p-values calculated with wild bootstrapped standard errors clustered at 6 broad industry categories.

Table 11: Different of frequencies of price adjustments on the frequency of wage adjustments. Using MW share and Lagged FWA as IVs.
Sample 2011-2014 & 2016.

	OLS				IV			
	All Changes		Positive Changes		All Changes		Positive Changes	
	Normal	Posted	Normal	Posted	Normal	Posted	Normal	Posted
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Second Stage								
Freq of Wage Ch	0.217**	0.279	0.131	0.152	0.274*	0.480*	0.138	0.325
	[0.040]	[0.139]	[0.194]	[0.201]	[0.097]	[0.096]	[0.436]	[0.480]
First Stage								
MW Share					-0.057	-0.057	-0.014	-0.014
					[0.112]	[0.112]	[0.655]	[0.655]
Lagged Fq Wage Ch					0.155**	0.155**	0.201**	0.201**
					[0.030]	[0.030]	[0.012]	[0.012]
Observations	350	350	350	350	350	350	350	350
Number of Industries	70	70	70	70	70	70	70	70
Number of Clusters	6	6	6	6	6	6	6	6
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Partial R2					0.065	0.065	0.079	0.079
Robust F					22.995	22.995	16.936	16.936

Note: This table reports the regression results of the frequency of adjustment of different price specifications on the frequency of wage changes plus industry and year fixed effects. The price specifications are normal prices (sales are filtered out), posted prices (include sales) and price hikes (considering only positive price changes). When the dependent variable is the frequency of price increases, the frequency of wage increases is used in the right hand side of the equation. All columns use data from 2011 to 2014 and 2016. In these years there was only one minimum wage adjustment. The first set of four columns adjust an OLS model. The latter set of four columns use a panel IV framework. The frequency of wage adjustments (increases) is instrumented with the share of minimum wage workers and lagged frequency of wage adjustments (increases). Figures in squared brackets are p-values calculated with wild bootstrapped standard errors clustered at 6 broad industry categories.

Table 12: Different of frequencies of price adjustments on the frequency of wage adjustments. Using MW share and Lagged FWA as IVs.
Sample 2013, 2014 & 2016.

	OLS				IV			
	All Changes		Positive Changes		All Changes		Positive Changes	
	Normal	Posted	Normal	Posted	Normal	Posted	Normal	Posted
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Second Stage								
Freq of Wage Ch	0.359	0.358	0.311	0.330	0.468*	0.544	0.234	0.374*
	[0.112]	[0.121]	[0.144]	[0.180]	[0.097]	[0.102]	[0.127]	[0.091]
First Stage								
MW Share					-0.104*	-0.104*	-0.081	-0.081
					[0.069]	[0.069]	[0.132]	[0.132]
Lagged Fq Wage Ch					0.150**	0.150**	0.194**	0.194**
					[0.036]	[0.036]	[0.015]	[0.015]
Observations	210	210	210	210	210	210	210	210
Number of Industries	70	70	70	70	70	70	70	70
Number of Clusters	6	6	6	6	6	6	6	6
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Partial R2					0.109	0.109	0.132	0.132
Robust F					15.612	15.612	45.886	45.886

Note: This table reports the regression results of the frequency of adjustment of different price specifications on the frequency of wage changes plus industry and year fixed effects. The price specifications are normal prices (sales are filtered out), posted prices (include sales) and price hikes (considering only positive price changes). When the dependent variable is the frequency of price increases, the frequency of wage increases is used in the right hand side of the equation. All columns use data from 2013, 2014 and 2016. In these years there was only one minimum wage adjustment. The first set of four columns adjust an OLS model. The latter set of four columns use a panel IV framework. The frequency of wage adjustments (increases) is instrumented with the share of minimum wage workers and lagged frequency of wage adjustments (increases). Figures in squared brackets are p-values calculated with wild bootstrapped standard errors clustered at 6 broad industry categories.

Table 13: Different of frequencies of price adjustments on the frequency of wage adjustments. Using Lagged FWA as IV.
Sample 2011-2014 & 2016.

	OLS				IV			
	All Changes		Positive Changes		All Changes		Positive Changes	
	Normal	Posted	Normal	Posted	Normal	Posted	Normal	Posted
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Second Stage								
Freq of Wage Inc	0.217**	0.279	0.131	0.152	0.208	0.505	0.114	0.308
	[0.040]	[0.139]	[0.194]	[0.201]	[0.347]	[0.358]	[0.437]	[0.477]
First Stage								
Lagged Fq Wage Adj					0.192**	0.192**	0.218***	0.218***
					[0.019]	[0.019]	[0.004]	[0.004]
Observations	350	350	350	350	350	350	350	350
Number of Industries	70	70	70	70	70	70	70	70
Number of Clusters	6	6	6	6	6	6	6	6
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Partial R2					0.051	0.051	0.078	0.078
Robust F					28.330	28.330	29.684	29.684

Note: This table reports the regression results of the frequency of adjustment of different price specifications on the frequency of wage changes plus industry and year fixed effects. The price specifications are normal prices (sales are filtered out), posted prices (include sales) and price hikes (considering only positive price changes). When the dependent variable is the frequency of price increases, the frequency of wage increases is used in the right hand side of the equation. All columns use data from 2011-2014 and 2016. In these years there was only one minimum wage adjustment. The first set of four columns adjust an OLS model. The latter set of four columns use a panel IV framework. The frequency of wage adjustments (increases) is instrumented with the lagged frequency of wage adjustments (increases). Figures in squared brackets are p-values calculated with wild bootstrapped standard errors clustered at 6 broad industry categories.

Table 14: Different of frequencies of price adjustments on the frequency of wage adjustments. Using Lagged FWA as IV.
Sample 2013, 2014 & 2016.

	OLS				IV			
	All Changes		Positive Changes		All Changes		Positive Changes	
	Normal	Posted	Normal	Posted	Normal	Posted	Normal	Posted
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Second Stage								
Freq of Wage Inc	0.359	0.358	0.311	0.330	-0.317	-0.158	-0.253	-0.043
	[0.112]	[0.121]	[0.144]	[0.180]	[0.458]	[0.547]	[0.144]	[0.687]
First Stage								
Lagged Fq Wage Adj					0.207**	0.207**	0.240***	0.240***
					[0.012]	[0.012]	[0.004]	[0.004]
Observations	210	210	210	210	210	210	210	210
Number of Industries	70	70	70	70	70	70	70	70
Number of Clusters	6	6	6	6	6	6	6	6
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Partial R2					0.074	0.074	0.108	0.108
Robust F					37.049	37.049	83.392	83.392

Note: This table reports the regression results of the frequency of adjustment of different price specifications on the frequency of wage changes plus industry and year fixed effects. The price specifications are normal prices (sales are filtered out), posted prices (include sales) and price hikes (considering only positive price changes). When the dependent variable is the frequency of price increases, the frequency of wage increases is used in the right hand side of the equation. All columns use data from 2013, 2014 and 2016. In these years there was only one minimum wage adjustment. The first set of four columns adjust an OLS model. The latter set of four columns use a panel IV framework. The frequency of wage adjustments (increases) is instrumented with the lagged frequency of wage adjustments (increases). Figures in squared brackets are p-values calculated with wild bootstrapped standard errors clustered at 6 broad industry categories.

Table 15: Frequencies of price adjustments on the frequency of wage adjustments and industry characteristics

	OLS				IV			
	All Changes		Positive Changes		All Changes		Positive Changes	
	Normal	Posted	Normal	Posted	Normal	Posted	Normal	Posted
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Second Stage								
Freq of Wage Change	0.332	0.297	0.301	0.303	1.299*	1.256*	1.278*	1.253*
	[0.164]	[0.219]	[0.219]	[0.248]	[0.054]	[0.080]	[0.067]	[0.067]
Labor Costs	-0.107*	-0.245	-0.049	-0.129	0.276	0.135	0.247	0.158
	[0.099]	[0.117]	[0.553]	[0.488]	[0.139]	[0.183]	[0.168]	[0.204]
First Stage								
MW Share					-0.126**	-0.126**	-0.119*	-0.119*
					[0.027]	[0.027]	[0.052]	[0.052]
Labor Costs					-0.367***	-0.367***	-0.274**	-0.274**
					[0.003]	[0.003]	[0.028]	[0.028]
Observations	210	210	210	210	210	210	210	210
Industries	70	70	70	70	70	70	70	70
Clusters	6	6	6	6	6	6	6	6
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Partial R2					0.067	0.067	0.062	0.062
Robust F					35.678	35.678	97.878	97.878

Note: This table reports the regression results of the frequency of adjustment of different price specifications on the frequency of wage changes plus the share of labor costs and industry and year fixed effects. The price specifications are normal prices (sales are filtered out), posted prices (include sales) and price hikes (considering only positive price changes). When the dependent variable is the frequency of price increases, the frequency of wage increases is used in the right hand side of the equation. All columns use data from 2013, 2014, 2016. In these years there was only one minimum wage adjustment. The first set of four columns adjust an OLS model. The latter set of four columns use a panel IV framework. The frequency of wage adjustment or the frequency of wage increases, depending the case, are instrumented with the share of minimum wage workers. Figures in squared brackets are p-values calculated with wild bootstrapped standard errors clustered at 6 broad industry categories.

Table 16: Cross-Section of Industries

	OLS				IV			
	All Changes		Positive Changes		All Changes		Positive Changes	
	Normal	Posted	Normal	Posted	Normal	Posted	Normal	Posted
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Freq of Wage Adj	0.439*	0.476	0.436**	0.436**	1.341*	1.613*	1.309*	1.443*
	[0.057]	[0.269]	[0.044]	[0.015]	[0.074]	[0.074]	[0.075]	[0.077]
Labor Costs	-0.265	-0.369	-0.165	-0.206	-0.176	-0.256	-0.101	-0.132
	[0.149]	[0.177]	[0.139]	[0.160]	[0.236]	[0.211]	[0.346]	[0.305]
Labor Force Adj Ease	-0.047	-0.051	-0.032	-0.031	-0.078	-0.090	-0.052	-0.054
	[0.386]	[0.487]	[0.331]	[0.427]	[0.315]	[0.304]	[0.295]	[0.301]
Informality Share	0.043	0.068	0.015	0.025	0.112	0.156	0.061	0.078
	[0.695]	[0.651]	[0.808]	[0.754]	[0.397]	[0.335]	[0.404]	[0.349]
Energy Intensity	0.054	0.035	0.034	0.025	0.101	0.095	0.060	0.055
	[0.413]	[0.683]	[0.412]	[0.614]	[0.318]	[0.361]	[0.405]	[0.385]
Imports Share	-0.020	0.029	-0.046	-0.027	-0.077	-0.043	-0.087	-0.074
	[0.826]	[0.800]	[0.522]	[0.584]	[0.521]	[0.680]	[0.121]	[0.222]
FX Pass-through	0.395**	0.625**	0.209*	0.307**	0.284	0.485*	0.127	0.213
	[0.029]	[0.022]	[0.065]	[0.025]	[0.343]	[0.078]	[0.454]	[0.266]
Industries	70	70	70	70	70	70	70	70
Clusters	6	6	6	6	6	6	6	6
Partial R2	0.333	0.353	0.328	0.351	0.573	0.573	0.504	0.504
Robust F	9.461	9.335	10.967	9.870	23.960	23.960	17.212	17.212

Note: This table reports regression results from a cross-section of industries. Averages by industries are calculated using data from 2013 to 2018. i.e. including years in our sample with none, one or more than one minimum wage adjustment. We regress the frequency of adjustment of different price specifications on the frequency of wage changes and a number of industry characteristics. The price specifications are normal prices (sales are filtered out), posted prices (include sales) and price hikes (considering only positive price changes). When the dependent variable is the frequency of price increases, the frequency of wage increases is used in the right hand side of the equation. The first set of four columns adjust an OLS model. The latter four columns use an IV framework. The frequency of wage adjustment or the frequency of wage increases, depending the case, is instrumented with the share of minimum wage workers. The share of minimum wage workers is also the average across years by industry. Figures in squared brackets are p-values calculated with wild bootstrapped standard errors clustered at 6 broad industry categories.