Wage and unemployment: evidence from online job vacancy data

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Wage and Unemployment:
Evidence from Online Job Vacancy Data

Abstract

This paper examines the relationship between labour market conditions and wage dynamics by exploiting a unique dataset of more than one million online job vacancies. We find a weak trade-off between aggregate wage inflation and unemployment. This link becomes more evident when the wage inflation is disaggregated at the sectoral and occupational level. The examination, using vacancy-level data, shows a negative correlation between offered wage and unemployment. The degree of wage elasticity, however, is different across regions and skill segments. Our findings suggest the importance of micro-level data's unique dimensions in examining the wage – unemployment relationship.

1 Introduction

For decades, the Phillips curve, which shows the negative relationship between inflation and unemployment, has been used as guidance for developing monetary policy by many central banks. Yet, there has been an ongoing debate about the extent to which this link still exists. Some studies acknowledge the flattening of the Phillips curve in advanced economies (Beaudry and Doyle, 2000; Roberts, 2006), while others show that the curve prevails, after accounting for other factors, such as inflation expectations or sectoral heterogeneity (Imbs et al., 2011; Coibion and Gorodnichenko, 2015; Moretti et al., 2019). Contributing to the debate is the development of the wage curve, which suggests a negative correlation between the level of wages and local unemployment. However, the wage curve has been also subject to criticisms related to potential biases and mismeasurements. Hence, despite the importance of both the Phillips and the wage curves, there is no consensus among scholars and policymakers on the existence and the strength of the link between wage and labour market conditions.

In this study, we shed light on this matter through a thorough analysis of the Phillips and the wage curves using micro-level data. More specifically, we exploit a unique dataset of online job vacancies from the Job Category on OLX.ua, a leading Ukrainian online advertisement platform. The data coverage is comprehensive, with more than one million job vacancies of 23 broadly defined categories posted daily over the 2016-2020 period in all regions of Ukraine. This rich dataset allows us to capture the country-wide labour market conditions more precisely. The various job dimensions contained in the dataset are also beneficial to our investigation of the *wage inflation – unemployment* link, as we can control for different sources of heterogeneity, which are not observable in the aggregated data. In addition, the data at vacancy level, coupled with outflows of workers to neighbouring countries, provide us with a unique identification framework to examine the *wage level – unemployment* relationship.

Using this dataset, we first construct an online wage index and show that this index is a reliable approximation of official statistics on the country-level wage growth. The examination of the Phillips curve is then undertaken at multiple levels of wage inflation, i.e., country, sectoral, and occupational levels. We find that, at the country level, the slope of the curve is weakly significant, even after controlling for inflation expectations.

However, the existence of the Phillips curve becomes more pronounced at the higher levels of disaggregation, suggesting the importance of heterogeneity. We next move to the vacancy level data and perform a detailed analysis of the wage curve. The estimates reveal a negative link between offered wages and unemployment, which is strong in terms of both statistical and economic significances. Further investigation reveals that wage cyclicity is a heterogenous parameter across different regions, as well as high-/low-skill occupations.

This study contributes to three main strands of literature. The first strand is the well-developed literature on the Phillips curve (Phillips, 1958), which documents the trade-off between inflation and unemployment rate. Although this concept has been widely used as one of the fundamentals for the development of many macroeconomic theories, its disappearance has been of concern to economists and policymakers. This flattening could be explained by the “anchored expectations” hypothesis (e.g., Bernanke, 2010; Blanchard, 2016; Hooper et al., 2019). More specifically, if inflation expectations have become anchored, due to the increasing creditability of modern central banks, inflation will become significantly less sensitive to business cycles. An alternative explanation is the downward nominal wage rigidity, due to workers’ bargaining power (Ball and Mazumder, 2011; Daly and Hobijn, 2014). There is also evidence that long-term unemployment is less likely to influence inflation, due to its detachment from the labour market (Llaudes, 2005; Gordon 2013; Krueger et al., 2014).

It should be noted that most evidence of the Phillips curve flattening is based on the macro-level data, which lack important labour market dimensions, e.g., income composition or job types. These dimensions, however, are often contained in the disaggregated data and are the source of variations in wage dynamics (Kudlyak, 2015). For example, the micro-level data show that there is a substantial difference in the cyclicity of wages across worker categories, e.g., newly hired workers, job stayers, and job movers (Shin, 1994; Carneiro et al., 2012; Kudlyak, 2014; Daly and Hobijn, 2017). Wage cyclicity also varies across income distribution groups, demographic groups, and other structural characteristics (Solon et al., 1994; Devereux and Hart 2006; Martins, 2007; Dapi, 2020). Overall, existing studies indicate that individual wages are highly procyclical, while aggregate average wages are subject to a composition bias. Thus, the examination of the Phillips curve using micro-level data could enable us to capture the important heterogeneity that cannot be observed in the macro-based analyses. The contribution of this study is that our Phillips curve examination utilizes a rich micro-level dataset. In doing this, we can shed new light on the extent to which micro evidence is informative in reflecting the (wage) inflation – unemployment relationship.

The second strand that this study contributes to is the literature on the wage curve – the negative link between the level of wages and local unemployment rate (Blanchflower and Oswald, 1994; 1995). Although the wage curve appears to be a robust empirical concept (Nijkamp and Poot, 2005) with supporting evidence from different countries, it has been subject to several criticisms.[1] Some such criticisms have not been fully addressed using the existing data. It is possible that the wage curve is a mis-specified labour-supply curve, rather than reflecting the wage setting behaviours. Further, an endogeneity bias may exist, as the level of wages may also affect the unemployment level. In addition, the estimates of the wage curve's slope could be sensitive to the choice of the dependent variable measures. For example, using earnings as a payment indicator may lead to bias, as an increase in earnings can be attributed to either higher wage or higher number of hours worked.[2]

The dataset of online job vacancies, coupled with the recent developments in the Ukrainian labour market, allow us to address at least partially these concerns. First, employing our unique data, we can control for labour market slackness/labour supply at the finely disaggregated levels, e.g., sector – region in the wage curve estimation. Thus, any significant estimates of unemployment, after controlling for the local labour supply/labour market slackness, would indicate the existence of a wage-setting curve. Second, although not perfect, we can use the growing opportunities for Ukrainian workers to work abroad as a source of exogenous variation in an instrumental variable framework. This approach allows us to check the robustness of the wage curve estimates.

This study also contributes to the recent studies that exploit data on job vacancies posted on online job search platforms, as an alternative source for labour economics research. Some studies apply textual analytics and machine learning techniques to extract important information, e.g., skill requirements, from the job description/advertisement

[1] See Blanchflower and Oswald (2005) for a detailed literature review.
[2] See Montuenga-Gómez and Ramos-Parreño (2005) for a detailed review of criticisms.

text (Deming and Kahn, 2018). The extracted information is then employed in the analysis of trends in skill demand or market segmentation (Hershbein and Kahn, 2017). Other studies use online vacancy data to examine the changes in aggregate labour markets and to create labour market indices. For instance, online data have been used to measure skill mismatch, labour supply/demand, and labour market concentration/tightness. Subsequently, these indices can be employed to investigate the employment effects of minimum wages, as well as to predict wages, the rate of mismatch unemployment, expected unemployment duration, and migration patterns (e.g., Adrjan and Lydon, 2019; Mamertino and Sinclair, 2019; Turrell et al., 2019; Azar et al., 2020). Our study complements this strand of literature by providing additional evidence for the usefulness of online vacancy data in capturing the aggregate labour market. Moreover, we show that this type of data can be utilized to understand, not only labour market dynamics, but also the broader macroeconomic issues, i.e., the link between wage setting and unemployment.

The rest of the paper is structured as follows. Section 2 describes the data employed for the analysis. In Section 3 we discuss our empirical strategies and results. Section 4 concludes and outlines the implications.

2 Data and sample

2.1 Online vacancy data

Data used in this study are taken from OLX.ua, one of the leading online advertisement platforms in Ukraine. According to Statista, in 2019, the number of OLX's visitors accounted for more than 30% of the total number of visitors of online marketplaces in Ukraine. It is also among the most visited websites in Ukraine, after Google, YouTube, and Facebook.[3] OLX job advertisements are divided into 25 categories and contain information about job locations, descriptions, salary, and job type. The detailed information allows us to control for regional, sectoral, occupational, and skill segment heterogeneity when exploring the link between wage setting and unemployment. Moreover, OLX.ua also provides us with data on the job seekers themselves, which is beneficial to our instrumental variable framework.

[3] See https://tinyurl.com/4nj4rn9h; https://blog.olx.ua/o-nas/; https://tinyurl.com/26ffw8kz (Accessed on March 06, 2021).

Although online vacancy data have unique features that can be exploited for economic research, there are several shortcomings that are worth noting. First, given that hiring wages are more cyclical than average wages (Bils, 1985; Devereux and Hart, 2006; Martins, 2007), one would expect a high degree of posted wage cyclicality in online vacancy data. Second, the data contain both ads that specify wages and those that do not specify wages. Since the former are likely to be low-skilled jobs (Brenčič, 2012), the estimation sample does not necessarily represent the Ukrainian labour market as a whole. Nevertheless, in the context of emerging market economies, such as Ukraine, where the representative surveys or sampled data are limited and lack granularity, the online vacancy data could still be useful for understanding the labour market (Kureková et al., 2015). For example, online vacancy data offer a timely and high-frequency indicator of detailed employment demand, such as demand by occupation, industry, or region level (Carnevale et al., 2014). Moreover, in the following sections, a comparison of the OLX data and the official data will be conducted to show that, although not perfectly, the former is highly correlated with the latter.

Our data cleaning process is as follows. First, since data coverage for the pre-2016 period is limited, we only retain data covering the 01/2016 – 12/2020 period for analysis. It should be noted that, similar to the other vacancy data sets in developed countries, such as Burning Glass Technology, the vacancies in the OLX data are new vacancies, i.e., a posting is recorded when it first appears (Azar et al., 2020). Second, we retain vacancies which i) are full-time jobs, ii) offer a monthly salary, and iii) have wages listed in Hryvnia (UAH). Third, all vacancies whose posted wages are lower than the 10th percentile (1,000 UAH) are excluded.[4] The offered wages are then trimmed at the 0.5th and 99.5th percentiles by region and by category. Finally, we exclude from the estimation sample all jobs listed in Crimea, or jobs of which the OLX category is “Early careers/Students” or “Work abroad”. After cleaning, our dataset contains more than one million vacancies belonging to 23 job categories.

Table 1 reports the overview of offered (posted) wages in our sample. Over the 2016-2020 period, we observe an increase in the average posted wage, which is generally

[4] This is to reduce the likelihood of misreporting bias. For example, firms might list their offered wages in foreign currencies (e.g., 100 USD, 200 USD, etc.) but do not specify this in the data fields. Thus, the wage data appear as 100 UAH or 200 UAH, although they should be 100 USD or 200 USD.

in line with the trend reported by the State Statistics Office. For example, the average offered wages in the OLX platform in 2017, 2018, 2019, and 2020 are 7,458 UAH (266.87 USD), 9,269 UAH (331.67 USD), 11,146 UAH (398.84 USD), and 12,565 UAH (449.61 USD), respectively. The corresponding official statistics are 254.24 USD, 317.29 USD, 375.86 USD, and 414.97 USD, respectively. One exception is the average posted wage in 2016, where the sample's statistic is significantly higher than the official statistic (6,972 UAH vs. 5,187 UAH). Nevertheless, this basic comparison suggests that online vacancy data closely tracks the aggregate labour market. In fact, it is possible that the online data could contain more information that is not observable in data collected using traditional methods. For example, our online vacancy data show that the upward trend in salaries is not limited to the high-paid jobs but occurs across wage distributions. In other words, it is not only the increase in the salaries of high-paid occupations which drives increases in the average offered wage.

Figure 1 illustrates the cross-regional variation in the average offered wages and average number of vacancies per population.[5] As can be seen, the top three regions, which have the highest ratio of online vacancies to population, include Kyiv (both capital and region), Dnipropetrovsk, and Odesa. This is to be expected, as these regions are the country's industrial, service, and financial centres. For example, Odesa is a tourism, seaport, and transport hub, while Dnipropetrovsk is a major industrial centre. Among all regions, Kyiv has the highest average and median posted wages (10,426 UAH and 9,000 UAH, respectively). Sumy and Zakarpattya, despite having the average wages in the top quartile, experience the largest wage dispersions. Moreover, the average posted wages in certain other regions, such as Donetsk, Luhansk, or Zaporizhzhya, are considerably lower than the sample average.

These variations across regions reflect the considerable regional heterogeneity in economic specialization, most of which has been inherited from the USSR. Specifically, Kyiv is the main financial centre of Ukraine, and it hosts the headquarters of the largest domestic and foreign owned companies. The South-East regions specialize in mining and manufacturing and had the highest level of productivity until the armed conflict in 2014. In contrast, the main economic sectors in most regions in Central and Western Ukraine

[5] More detailed statistics are reported in Appendix Table 1.

are agriculture, tourism, and recreation. Moreover, the key sectors within a regional group can also vary significantly. For instance, compared to other regions in Central Ukraine, where agriculture is the main economic sector, Odesa is a major transport hub, which makes a substantial contribution to the Ukrainian economy.[6]

Additionally, the recent geo-political events have affected the local labour markets in Ukraine. Due to the tight supply chains and production linkages with Russia, which were negatively affected by the armed conflict in 2014, the Eastern regions, particularly those in the conflict zone, have experienced a significant business outflow and a reduction in productivity. At the same time, Ukraine and Russia have imposed trade and transit restrictions, bilaterally. These, in turn, have had a negative impact on the Eastern regions' labour markets. As reported by OECD (2018), more than 1.6 million workers in the Donbas regions lost their jobs, mainly in mining, machine building, other heavy industry sectors, and services.[7] A vast majority of the so-called internally displaced persons moved to nearby regions, close to their home regions, or to Kyiv to find new jobs. Furthermore, the traditional links with Poland, coupled with the recent relaxation of legal requirements, has created more opportunities for Ukrainians to find jobs abroad. Consequently, there is an increase in the number of emigrants moving from the East to the West and from the West to other European countries. Further cooperation and gradual progress towards increased European integration have made the local markets in Western and Central Ukraine more competitive and more dynamic.

Further statistics by job category are presented in Table 2. Job categories with the highest number of vacancies are Retail/Sales/Purchases, Transportation/Logistics, Bars/Restaurants, Construction, and Production/Energy. The dominance of vacancies in these categories can be explained by the recent booming of the related industries, as well as the increasing demand for labour in these industries from neighbouring countries, such as Poland. As noted previously, more job offers do not come with higher wages. The average wages offered in the Retail/Sales/Purchases and Bars/Restaurants categories are, in fact, at the bottom of the average wage distribution. Conversely, vacancies in the Transportation/Logistics, Construction, and Production/Energy categories offer the

[6] See https://tinyurl.com/2vs3ez4f for more details on regional diversity in Ukraine (Accessed on March 6, 2021).
[7] See https://tinyurl.com/fzmcz5cw (Accessed on March 6, 2021).

highest wages. This difference could be due to the composition of jobs within each category. More specifically, the most requested job titles in our sample belong to the Retail/Sales/Purchases and Bars/Restaurants categories, however the offered wages of these occupations are relatively low (see Table 3). In other words, the Retail/Sales/Purchases and Bars/Restaurants categories are dominated by low-paid jobs, leading to both categories exhibiting an overall low salary.

2.2 Other data

Different series of unemployment indicators are also used, including (1) the monthly aggregated unemployment rate and (2) the monthly statistics of the number of unemployed, by regions and at country level. Since the former series was discontinued in 2019, we use the latter series as the alternative measure of unemployment, and also to impute the monthly unemployment rate. More specifically, we assume that the size of labour force is stable within a quarter and construct the imputed unemployment rate as the percentage of monthly unemployed in the quarterly labour force. This is done at both the country and regional levels. Figure 2 shows that the imputed unemployment series closely tracks the official statistics, with a correlation of 99.7%.

Given the importance of the forward-looking Phillips curve where inflation expectation is taken into account, we also obtain the inflation expectation data from the National Bank of Ukraine for our analysis. This dataset contains information on the inflation expectation of businesses, banks, households, and financial analysts. Regarding the first and second indices, the National Bank of Ukraine (NBU) surveyed 700 non-financial firms, representing the economy in terms of main economic activities, size, and number of employees surveyed, as well as all commercial banks. The respondents are asked “What change do you expect in prices of consumer goods and services in Ukraine over the next 12 months?”. The survey is conducted on a quarterly basis. In 2014, the NBU started a new survey of inflation expectation across the different time horizons of 21 financial analysts (professional forecasters) on a monthly basis. At the same time, the inflation expectation question was added to the Household Consumer Confidence Survey, which is also conducted on a monthly basis.

2.3 *Online wage index vs. official statistics*

As mentioned earlier, a concern related to the online vacancy data is that the data are not representative of the whole labour market. In this section, we perform a preliminary check to determine whether the OLX data can track the official labour market statistics, and thus, can be used as the alternative data source for investigating the wage – unemployment link. More specifically, we will discuss the methodology used to construct the OLX-based wage inflation and compare it with the official statistics.

Similar to Martins et al. (2012), we employ a two-month rolling-window hedonic wage model to construct the OLX wage inflation indices.

$$W_{it} = \alpha + \beta_t Month_t + FEs + \varepsilon_{it} \qquad (1)$$

where W_{it} is the natural log of offered wage for vacancy i posted on date t. $Month$ is a dummy variable, which is equal to one, if date *t* is in the current month and zero if date *t* is in the previous month. *FEs* is a vector of categorical and regional fixed effects. The estimated β_t can be considered the net-of-fixed effects measures of wage growth.

We first estimate Model (1) for all vacancies to obtain the country-level wage index, which accounts for both regional and categorical fixed effects. Next, Model (1) is estimated for each category in cases when i) regional fixed effect is controlled for and ii) regional fixed effect is not controlled for. Similarly, the category – region level wage index is also estimated. Finally, the occupation – region level wage index is obtained by estimating Model (1) for each job title – region pair, controlling for categorical fixed effects.

To examine the predictive power of our category-level wage index in predicting the official wage inflation, we use a linear model of the following form:

$$\Delta \mathrm{W}_t^{official} = \alpha + \Delta \mathrm{W}_{ct}^{OLX} \beta + \varepsilon_t \qquad (2)$$

where $\Delta W_t^{official}$ is the monthly wage growth reported by the statistics office. ΔW_{ct}^{OLX} is a vector of *monthly* wage inflation by category obtained from Model (1), i.e., the estimated β_t. It should be noted that both $\Delta W_t^{official}$ and $\Delta \mathrm{W}_{ct}^{OLX}$ are seasonally adjusted.

Model (2) is estimated using two approaches. In the first approach, we adopt the least absolute shrinkage and selection operator (LASSO) method, a machine learning method used to select the most important category-level wage growth indices contributing to the official country-level index. In this exercise, we only include the categories in which wage indices are observed for the full sample period. The LASSO method minimizes the residual sum of squares subject to a penalty (λ) on the absolute size of coefficient estimates (Tibshirani, 1996; Ahrens et al., 2018). As λ increases, more coefficients are set to zero and dropped, and thus, the variance decreases at the expense of increasing bias. The variance bias trade-off helps to improve the degree of prediction accuracy of the model.[8]

In the second approach, we use the vacancy weighted OLX indices as the predictors which are computed as follows:

$$\Delta \mathrm{W}_{ct}^{weighted\ OLX} = \frac{Vacancies_{ct}}{Total\ vacancies_t} \times \Delta \mathrm{W}_{ct}^{OLX} \tag{3}$$

The correlation between the predicted country-level wage inflation index obtained from Model (2) and the official statistics is shown in Figure 3. As can be seen, the online-based wage index is closely matched with the official wage index, with a correlation of 61-80%. This reasonably high correlation suggests that the online vacancy data can be exploited to understand wage setting and wage inflation in Ukraine.

3 Empirical analysis

3.1 The Phillips curve

3.1.1 <u>The Phillips curve at the country level</u>

To examine the link between *inflation* and *unemployment* using monthly aggregate data, we employ the following model:

$$\Delta P_t = \alpha + \beta U_t + \varepsilon_t \tag{5}$$

where ΔP_t is i) the monthly official wage growth or ii) the estimated monthly wage growth obtained from estimating Model (1). For comparison, Model (5) is also estimated using

[8] To choose the optimal penalty level, we use the Akaike Information Criterion (AIC).

the monthly official CPI as a dependent variable. U_t is the monthly unemployment rate. Based on the staggered wage setting model of Erceg et al. (2000), in the alternative Phillips curve specification, we incorporate the inflation expectation indicator, $E(\Delta P_{t+12})$, as an additional covariate. We use the financial analysts' long-horizon inflation expectation (i.e., 12-month ahead inflation expectation) for this forward-looking Phillips curve specification.

Results reported in Table 4 show the negative slope of the Phillips curve for the nominal Headline CPI inflation and the OLX-based wage inflation. In particular, an increase of 1 percentage point in the monthly unemployment rate leads to a reduction of 0.4-0.5 percentage points in the Headline CPI inflation rate. Similarly, the OLX-based wage inflation rate decreases by 1.46 percentage points, with a 1 percentage point increase in unemployment rate. However, there is no evidence of the Phillips curve for the official wage inflation, regardless of whether the basic or the forward-looking Phillips curve specifications are estimated. The estimations of the forward-looking Phillips curve, using different inflation expectation indicators, yield quantitatively similar results (Appendix Table 2).

Setting the statistical significance aside, the findings support the existing studies, which show that newly hired wages are highly responsive to business cycles (Bils, 1985; Devereux and Hart, 2006; Martins, 2007). Moreover, despite the potential bias due to the small sample size (T = 57), it is still worth noting that the results are in support of existing literature, which find that the Phillips curve has been identified in developed countries in recent years (e.g., Gordon, 2013; Coibion and Gorodnichenko, 2015; Jorgensen and Lansing, 2019; Moretti et al., 2019). For example, Hindrayanto et al. (2019) show the estimated slope of -0.6 for the Phillips curve in Euro area over the 1985 – 2017 period. The similar estimates are observed for the Phillips curve in Germany, the Netherlands, and France, while the estimated slopes for Italy and Spain are smaller (-0.15 and -0.35, respectively).

3.1.2 The Phillips curve at the disaggregated levels

In this section, we use the disaggregated OLX wage inflation to investigate the inflation – unemployment relationship. Specifically, Model (5) is re-estimated using the i) category level wage index, ii) category – region level wage index (Table 5), and iii) occupation (job title) – region level wage index (Table 6). In addition, in the investigation of the Phillips curve at the occupational – regional level, two different approaches are employed to estimate the wage inflation index. The first approach is the two-month rolling-window hedonic wage model, described in Section 2.3. The second approach is the cell median method: for each occupation – region – month unit, we use the median salary to measure monthly wage growth, conditional on each unit having at least ten observations.

Consistent with the previous results, evidence of the Phillips curve is identified. Moreover, the slope of the curve becomes steeper, the higher the levels of disaggregation. Specifically, an increase of 1 percentage point in unemployment rate is related to a 1-1.6 percentage point decrease in the category-specific wage growth. Similarly, the occupation-specific wage growth decreases by 1.1-1.4 percentage points, with a 1 percentage point increase in unemployment rate. The slope is marginally steeper when we consider the categorical – regional Phillips curve or the occupational – regional Phillips curve (the coefficients are between -1 and -1.7). These findings are in line with the previous studies, which show a sizeable difference in the slopes of the aggregate Phillips curve and the sectoral - regional Phillips curve (Imbs et al., 2011; Byrne et al., 2013; Fitzgerald and Nicolini, 2014; Hooper et al., 2019).

To this end, our results contribute to the existing literature and confirm the importance of heterogeneity in the examination of wage dynamics (Leith and Malley, 2007; Byrne et al., 2013). More specifically, the examination of the Phillips curve, using the aggregate data, assumes the existence of homogenous wage stickiness across sectors and regions. However, this assumption may not always hold, as there has been evidence to suggest a significant sectoral variation in the Phillips curve slope (Imbs et al., 2011; Luengo-Prado et al., 2018). Additionally, the aggregate wage inflation does not take into account the composition effects and unobserved occupational, sectoral, or regional heterogeneity. That is, the composition of occupations or sectors in a local labour market varies across regions, e.g., some local markets are dominated by low-skill occupations, while some others are dominated by high-skill ones. Thus, the aggregate inflation may be subject to composition and/or aggregation biases, which could mask the wage responsiveness (Verdugo, 2016). Using the alternative sources of micro-level data, such as the online vacancy data, could help to address such concerns. Specifically, the online vacancy data will allow for the estimation of the wage inflation at the occupational, regional, and occupational – regional level, while accounting for various heterogeneity.

3.2 The wage curve

3.2.1 Empirical specifications of the wage curve

To examine the link between level of wages and unemployment, we employ the following wage regression.

$$lnW_{icrt} = \alpha + \beta lnU_t + Controls_{it}\delta + \gamma lnJobs_{crt} + FEs + \varepsilon_{icrt} \tag{6}$$

Where *i*, *c*, *r*, and *t* refer to vacancy *i*, category *c*, region *r*, and month *t*, respectively. *lnW* is the natural log of posted wage. *lnU* is either (1) the natural log of the country-level unemployment rate or (2) the natural log of the number of country-level unemployed in month *t*. *Controls* is a vector of vacancy-specific variables to control for the quality of job description. These variables include i) the natural log of one plus the number of words in the job description (*words*); ii) the quadratic form of *words* ($words^2$); and iii) the natural log of one plus the number of sentences in the job description (*sentences*). We argue that the longer the description, the more likely it is to contain more detailed information and/or requirements that can determine the offered salaries. *lnJobs* is the natural log of the number of category-region specific OLX vacancies (excluding jobs abroad) in a month. *FEs* is a vector of various fixed effects, i.e., month of year, year, day of week, category, and region.[9]

To address the potential biases (e.g., aggregation bias, composition bias, or simultaneity bias), different specifications of Model (6) are employed. More specifically, to address the endogeneity concern, in addition to the fixed effect (FE) estimation, Model (6) is also estimated using an instrumental variables (IV) estimator, in which lnU is the endogenous variable. The choice of instrument is motivated by Elsner (2013) who shows that wage change is an important channel to absorb the labour supply shocks in the origin countries caused by the 2004 EU enlargement. Hence, we use the natural log of one plus the number of vacancies to work abroad (abroad jobs) as the instrument. An increase in the number of working abroad vacancies would directly lead to an increase in the number

[9] Our results are similar if the control variables are excluded from estimations. These results are available upon request.

of emigrants, and thus, a negative labour supply shock to the domestic labour market which in its turn affects wages offered by domestic firms.[10]

Since the existing evidence of the wage curve relies on data on individual salaries, there is the issue of time-variant, but unobserved, individual (labour) characteristics, e.g., knowledge and skills that change over time and could affect earnings. However, this is not a concern for our setup, since we use data on wages offered by firms. Thus, other factors that could affect wage, but are not vacancy-specific, e.g., technological development of the industry, can be captured by time, regional, and occupational fixed effects.

The existing literature has also cast doubt on the validity of the wage curve, i.e., whether it is purely a mis-specified labour supply curve and/or a mis-specified Phillips curve. To address this concern, we add into Model (6) an indicator of monthly labour market slackness/tightness for a given job category (*c*) – region (*r*) pair (*slack*). It is measured as the ratio of one plus the number of job seekers, to one plus the number of vacancies, which indicates the search and matching frictions. Thus, if the wage curve is simply a mis-specified labour supply curve, or a mis-specified Phillips curve, then the estimated coefficient on *lnU* should be less (if not) statistically significant with this inclusion.

Furthermore, we estimate the modified Model (6), in which the autoregressive term of log wage, i.e., lagged log of wage, is included as a regressor. This exercise is done at the occupation – region – month level through the cell mean method. More specifically, data on offered wage and control variables in Model (6) are aggregated into cell means, where each cell is an occupation – region – month pair. In this analysis, the modified Model (6) is estimated using (1) the fixed effect estimator and (2) the first difference-GMM dynamic panel estimator.

Finally, we estimate Model (6) using both nominal wage and real wage to account for the business cycle variation in local prices.

[10] The OLX data have "Work Abroad" as a category across all regions. Hence, our instrument is measured at the region-month level.

3.2.2 What do vacancy-level data tell us about the wage curve?

Table 7 provides evidence of the wage curve: the estimated coefficients on unemployment indicators are negatively significant in all regressions. However, there are differences in the magnitude. In the baseline regressions (Columns 1 and 3), the estimated slopes are -0.25 and -0.28, respectively. Similar results are observed when we include the slackness indicator (Columns 2 and 4). That is, a 1% increase in the unemployment rate is related to a decrease of 0.28-0.3% in offered wages. It is worth noting that our estimates of unemployment are relatively comparable to those in other European countries (e.g., Wagner, 1994; García-Mainar and Montuenga-Gómez, 2003). For instance, Montuenga-Gómez et al. (2003) show that the estimated slope coefficients of the wage curve for France, Spain, and UK are -0.158, -0.235, and -0.244, respectively.

Regarding the IV estimations (Columns 3 and 6), the results of the under-identification and weak identification tests (LM test and F-test) suggest that the instrument is relevant. Additionally, the first stage results reported in Appendix Table 3 show that a higher number of abroad jobs has a negative impact on unemployment. In other words, more working abroad vacancies provide opportunities to work for individuals who might be otherwise unemployed, leading to a reduction in the home country's level of unemployment. However, with the F-statistics of around 11-12, our instrument could still be considered a weak instrument. Moreover, there could be a concern about the exclusion restriction in our setting. For example, one could argue that certain types of workers are in high demand by both domestic and foreign firms. Thus, domestic firms might increase their wage offers to attract and retain these types of workers, as the number of offers from foreign firms increases.[11] Nevertheless, the estimation results using the IV estimator are still useful for comparison and for checking robustness, although one should interpret the results with caution.[12] More specifically, we still observe the existence of the wage curve, but the estimated slopes are significantly steeper than the slopes estimated in the baseline estimations.

[11] We thank the anonymous referees for this suggestion.
[12] In a further robustness check, we include the natural log of the number of job seekers who look for abroad jobs as another instrument (Appendix Table 4). Our baseline results are similar with the inclusion of this instrument.

Our analysis of the wage curve, adding in the lagged log of wage, suggests the co-existence of the Phillips curve and the wage curve (Table 8). That is, the coefficients on both lagged log of offered wage and unemployment are statistically significant and the results are stronger for the nominal wages. The slope of the wage curve is comparable to those reported previously. Further, the estimated autoregressive term of log of wage is below unity (between 0.36-0.54). These results suggest that the wage curve is not the mis-specified Phillips curve, but rather reflects the negative relationship between the wage level and unemployment, where a certain degree of wage stickiness exists.

Three main conclusions can be drawn from the above findings. First, the steeper slope in the IV estimations suggests the importance of controlling for the endogeneity bias when investigating the wage curve. Second, the existence of the wage curve does not "disprove" the existence of the Phillips curve. In fact, our results point to a reconciliation between these curves.

3.2.3 The wage curve and heterogeneity

In this section, we investigate the extent to which the wage curve is subjected to various types of heterogeneity. First, we aim to explore whether the curve's slope is different across occupations that require different levels of skills. More specifically, given skill premia, the wages of low-skill jobs are expected to be in the left tail of the wage distribution. Thus, given the same percentage of wage increase, it would be less costly (in terms of the level of wage increase) for the firms to raise the wages of the low-skill jobs.[13] Furthermore, in line with Thurow's job competition model (Thurow, 1975), competition tends to be higher in the low-skill segment of the labour market, as the high-skilled workers can also compete for jobs in this segment, but the opposite does not hold. This, consequently, eases the wage pressure (for low-skill jobs) during the tight labour market. Taken together, we posit that the low-skill occupations' wages are less rigid.

Table 9 reports the results of this analysis where we re-estimate Model (6) on the sub-samples of low- and high-skill occupations, as well as employing the skill-specific unemployment rates. Such measures are constructed using the monthly number of unemployed by occupations. Borrowing the classifications of jobs by skills used in

[13] For example, the low-skill job's wage is $1,000 and the high-skill job's wage is $5,000. An increase of 10% is translated into a raise of only $100 for the low-skill job but a raise of $500 for the high-skill one.

previous studies (e.g., David and Dorn, 2013), we classify job titles/occupations that typically do not require a college education, e.g., drivers, baristas, or security guards, as the low-skill occupations. In contrast, those that require college education, e.g., economists, programmers, legislators, or managers, are classified as high-skilled occupations. However, a limitation of the unemployment data by occupations is that the series is only available for the 2018 – 2020 period. Thus, for comparison, we also perform the analysis using the aggregate unemployment.

The results show that the low-skill jobs' wage is more flexible than that of the high-skill jobs. More specifically, the low-skill jobs' wage decreases by 0.19-0.23% with a 1% increase in the aggregate unemployment rate, while the decline in the high-skill jobs' wage is 0.15-0.19%. Similarly, the elasticity of low-skill wage to low-skill unemployment rate is around 0.12%, while the elasticity of high-skill wage to high-skill unemployment rate is 0.08-0.1%. The finding is in line with other studies (Hoynes et al., 2012; Borjas, 2017) which show that labour market outcomes, e.g., the earnings of low-education workers (i.e., low-skilled workers) are more affected by the economic downturns or slack labour markets. The result also highlights the importance of skill composition in examining the wage – unemployment link.

Second, we aim to capture the effects of regional heterogeneity by re-estimating Model (6) on sub-samples of different regions in Ukraine, i.e., Western, Central, and South-East regions, as well as Kyiv city/region. The unemployment measures used in this analysis are at the regional level. The results in Table 10 indicate that offered wages in Western Ukraine are mostly procyclical, with the estimated slope of around -0.3. The wage elasticities to unemployment in Kyiv and Central Ukraine are relatively similar (around -0.1). In contrast, we do not find evidence of the wage curve for the South-East regions.

This difference could be explained by the geographical locations and economic specialization of these regions, as well as the recent political developments documented in Section 2.1. Since the Western and Central regions, including Kyiv, share borders with the Central and Eastern European countries, they are more prone to the short- and long-term emigration of the workforce to the neighbouring countries, e.g., Poland. This outflow of Ukrainian workers is likely to be augmented by the economic/geopolitical crisis in 2014-2015. Another factor that contributes to the growth of emigration is the easing of Polish law on the employment of foreign nationals in 2014, which facilitates the possibility of staying and seeking jobs in Poland for Ukrainian citizens. Additionally, in 2017, a visa-free agreement was made between Ukraine and the Schengen area, which allows the free movement of Ukrainian citizens across all Schengen countries. This agreement could also potentially increase the employment opportunities for Ukrainian workers in these countries.

In contrast, the South-East regions, historically, had tight linkages with Russia in terms of economic activities and labour outflows, which have been negatively affected by the geopolitical crisis that began in 2014. Moreover, following the onset of the geopolitical unrest, Ukrainian banks have reduced their lending to businesses in the areas close to the conflict zone (Pham et al., 2021), which could have negative impacts on firms' investments and productivity. Taken together, during the examined period, the offered wages in the West and Central Ukraine are more flexible, as firms have to adjust wages quickly in response to the more dynamic local labour markets. Meanwhile, the South-East regions have a higher degree of wage stagnation, due to the decreasing levels of productivity, decreasing job opportunities, and increasing labour outflows to the West.

3.2.4 Effect of visa-free regime

To examine the extent to which the visa-free regime, that allows Ukrainian citizens to enter Schengen countries without a visa, affects the elasticity of the wage curve, we incorporate into Model (6) the interaction term between unemployment indicator and post-visa regime indicator (*Visa free*). This indicator is a categorical variable, which is equal to 0 for the January 2016 – June 2017 period, and equal to 1 for the July 2017 – December 2019 period (the visa-free regime came into effect in July 2017). We exclude the 2020 period from this analysis, since 2020 features the COVID-19 pandemic, which has negatively affected the socio-economic conditions. The impact of COVID-19 on the Ukrainian labour market is out of the scope of this study and is reserved for future research.

As can be seen in Table 11, we find weak evidence of the change in the wage curve's elasticity after the visa-free regime came into effect. This lack of sensitivity of the wage curve to the regime can be explained by several factors. First, this regime was not the first policy change to open up opportunities for Ukrainian workers to work abroad. In May 2014, the Polish government had relaxed the legal eligibility criteria, usually required for Ukrainian citizens to live in Poland and to find a job, which has since led to a notable outflow of Ukrainian workers to Poland. As shown in the report by Jaroszewicz (2018), the number of statements of intention to employ Ukrainian citizens and the number of work permits issued to Ukrainian citizens doubled in 2015 and the quantity continues to grow. Second, while the visa-free regime in 2017 might provide workers with opportunities to find a job in relatively more developed host countries, job searching in the host countries comes with certain difficulties, related to languages or skill requirements, that are not easy to overcome. In addition, Ukrainians still need to apply for the working visa to officially take the job, which creates a barrier between successfully finding a job and starting work.

4 Conclusion

Recent years have witnessed the continuing debate among economists and policymakers about whether, and the extent to which, the relationship between wage and unemployment (still) exists. Both the supporting evidence and the critics of the two main phenomena of the link, the Phillips curve and the wage curve, have been presented. For example, some studies lend support to the trade-off between inflation, or wage growth, and the slack/tightness of labour market, i.e., the Phillips curve. At the same time, there are criticisms that potential biases may arise from the use of aggregated data, calling for further investigation using micro-level data. Similarly, while the wage curve, the negative correlation between wage level and unemployment, has provided an alternative view on the matter of wage – labour market conditions, there have also been concerns about the model used to estimate the curve.

Given the importance of the Phillips and wage curves in monetary policymaking, there is a need for a better understanding of the relationship that the curves represent. In this study, we pursue this objective and exploit the new dataset of online vacancies to perform a rigorous analysis of the curves. More specifically, we utilize the unique features of more than one million jobs posted on OLX.ua, a leading advertisement website in Ukraine, to examine the link between unemployment and wage dynamics at various aggregation levels and dimensions.

Our results are as follows. First, online vacancy data can be used to approximate the official statistics on wage dynamics in Ukraine. Second, at the country level, the evidence of the Phillips curve is somewhat weak. However, when different types of heterogeneity, e.g., sectoral or occupational heterogeneity, are taken into account, the Phillips curve becomes more evident. Finally, we show the strong and persistent existence of the wage curve. Yet, there are differences in the (statistical and economic) significance of the curve's slope, when we (i) control for regional difference or skill composition of the labour market, (ii) address the misspecification concerns, and (iii) address the endogeneity bias.

The findings in this study suggest that the link between wage and unemployment exists, regardless of whether the wage inflation or the level of wage is considered. Hence, it is plausible to use economic theories, built on this link, for policymaking. Nonetheless, it remains important to account for potential biases in order to obtain the most accurate estimates of the relationship, and thus, a better policy. One way to do this is to take advantage of the new and rich sources of labour market data, e.g., online vacancies, in the Phillips curve/wage curve analysis. Using such new data sources, economists and policymakers will be able to observe and analyse wage dynamics in real time. This, evidently, cannot be done using the traditional data, which are aggregated and updated with lags.

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Tables

Table 1. Summary statistics of wages over time

	(1)	(2)	(3)	(4)	(5)	(6)
	Official	Mean	P25	P50	P75	SD
Full sample	8,652	9,005	4,500	7,500	11,500	6,206
By year						
2016	5,187	6,972	3,000	4,750	8,000	6,157
2017	7,105	7,458	4,750	6,135	8,500	4,728
2018	8,867	9,269	6,000	8,000	11,000	5,084
2019	10,504	11,146	7,500	10,000	13,500	5,717
2020	11,597	12,565	8,000	11,000	15,000	6,336
By quarter of year						
Q1	7,911	8,173	4,000	6,750	10,000	5,767
Q2	8,418	8,142	4,000	6,500	10,000	5,724
Q3	8,825	9,257	4,750	7,500	12,000	6,366
Q4	9,455	10,362	5,500	9,000	13,500	6,577

Notes: This table shows the summary statistics of wages (in UAH) in our sample. Column 1 shows the average wages reported by the statistics office. Columns 2-5 show the average, 25th percentile, median, and 75th percentile OLX posted wages, respectively. Column 6 shows the standard deviation of OLX posted wages.

Table 2. Number of vacancies and average wages by categories

	(1)	(2)	(3)	(4)	(5)	(6)
	Vacancies	Posted wage				
	Total	Mean	P25	P50	P75	SD
Retail/Sales/Purchases	256,496	7,069	4,001	6,100	9,100	3.935
Transportation/Logistics	151,408	11,227	5,788	10,000	15,000	7.122
Bars/Restaurants	126,951	7,122	4,000	6,000	9,163	4.018
Construction	113,214	12,956	6,500	11,000	17,500	8.422
Others	108,030	10,339	5,000	9,000	14,975	6.477
Production/Energy	90,072	10,208	5,500	9,000	14,000	5.801
Beauty/Fitness/Sports	43,315	6,994	3,500	6,000	9,500	4.688
Services	42,724	7,708	3,900	6,001	10,000	5.328
Security/Safety	33,440	5,584	3,001	4,550	7,401	3.310
Home assistance service	28,025	10,732	4,500	8,000	15,000	8.295
Law and Accounting	11,992	6,982	4,000	6,000	9,000	4.003
Marketing/Advertising/Design	11,359	7,756	4,500	6,500	10,000	4.849
Medicine/Pharmacy	10,840	6,253	3,000	5,000	8,000	5.006
Secretary	10,053	6,623	3,750	5,500	8,500	4.104
IT/Telecom/Computers	9,198	8,252	4,200	6,500	10,000	6.141
Real estate	9,011	7,717	4,000	6,050	10,000	5.366
Tourism/Recreation/Entertainment	8,588	12,948	7,250	10,250	17,000	7.975
Education	8,543	6,061	2,500	4,400	7,500	5.263
Agriculture/Agribusiness/Forestry	4,725	10,015	6,000	8,750	12,000	5.739
HR	3,055	10,776	7,000	10,000	13,500	5.511
Telecommunications/Communication	2,895	9,667	6,000	8,500	12,000	4.961
Banks/Finance/Insurance	2,530	9,342	6,000	8,250	11,000	4.668
Culture/Art	2,091	7,662	3,500	6,000	10,000	6.390

Notes: This table reports statistics on the posted wages (in UAH) and the number of vacancies by OLX job categories. Column 1 shows the total number of vacancies. Columns 2-5 show the average, 25th percentile, median, and 75th percentile posted wages, respectively. Column 6 shows the standard deviation of posted wages.

Table 3. Number of vacancies and average salaries by top 10 job titles

	(1)	(2)	(3)	(4)	(5)	(6)
	Vacancies	Posted wage				
	Total	Mean	P25	P50	P75	SD
Seller	113,250	6,856	4,000	6,000	9,000	3,923
Driver	69,730	12,792	7,000	11,500	18,000	7,511
Manager	37,955	9,408	5,100	8,000	12,000	5,428
Cook	35,609	8,117	5,000	7,150	10,500	4,397
Consultant	28,980	5,900	3,750	5,000	7,425	3,168
Assistant	27,231	8,066	4,500	7,000	10,000	5,079
Loader	26,669	7,240	4,450	6,669	9,500	3,682
Worker	24,016	10,122	5,000	9,000	14,000	6,293
Handyman	23,205	8,860	5,000	7,800	11,500	5,267
Security guard	22,771	4,846	3,000	4,000	6,000	2,660

Notes: This table reports statistics on salary (in UAH) and number of vacancies for top 10 job titles that have the highest number of vacancies. Column 1 shows the total number of vacancies. Columns 2-5 show the average, 25th percentile, median, and 75th percentile posted wages, respectively. Column 6 shows the standard deviation of posted wage.

Table 4. The Phillips curve (country level)

	(1)	(2)	(3)	(4)	(5)	(6)
	CPI inflation		Official Wage inflation		OLX Wage	
	Nominal	Adjusted	Nominal	Adjusted	Nominal	Adjusted
U	-0.5466***	-0.4278*	-1.1614	-1.4526	-1.4593**	-0.9908
	(0.1738)	(0.2158)	(1.7267)	(2.0467)	(0.6797)	(0.6810)
$E(P_{t+12})$		0.0761		-0.1864		0.2998*
		(0.0754)		(0.6332)		(0.1607)
Observations	57	57	57	57	57	57
R-squared	0.0913	0.1171	0.0066	0.0091	0.0475	0.0768

Notes: This table reports results for the baseline Philips curve (Columns 1, 3, and 5) and the forward-looking Phillips curve (Columns 2, 4, and 6) at country level. The dependent variable is the inflation rate measured by i) the monthly official CPI (Columns 1-2), ii) the monthly official wage growth (Columns 3-4), and iii) the country-level OLX wage growth obtained from estimating Model (1) (Columns 5-6). *U* is the monthly unemployment rate at country level. $E(P_{t+12})$ is the 12-month ahead inflation expectation of financial analysts obtained from the NBU Surveys. Robust standard errors are reported in parentheses. *, **, and *** denote significance at 10%, 5%, and 1% significance levels, respectively.

Table 5. The Phillips curve (categorical and categorical - regional level)

	(1)	(2)	(3)	(4)
	Category		Category - Region	
	Nominal	Adjusted	Nominal	Adjusted
U	-1.5520***	-1.0396*	-1.6379***	-1.0347*
	(0.5404)	(0.5724)	(0.5517)	(0.5499)
$E(P_{t+12})$		0.2512**		0.2885**
		(0.1210)		(0.1175)
Obs.	1,244	1,244	20,330	20,330
R-squared	0.0257	0.0291	0.0034	0.0040

Notes: This table reports results for the baseline Philips curve (Columns 1-3) and the forward-looking Phillips curve (Columns 2-4) at categorical and categorical - regional level. The dependent variable is (i) categorical level wage index (Columns 1-2) and (ii) categorical - regional level wage index (Columns 3-4). *U* is the monthly unemployment rate at country level. $E(P_{t+12})$ is the 12-month ahead inflation expectation of financial analysts obtained from the NBU Surveys. In Columns 1-2, month of year and category fixed effects are included but not reported. In Columns 3-4, month of year, category, and region fixed effects are included but not reported. Standard errors clustered by month are reported in parentheses. *, **, and *** denote significance at 10%, 5%, and 1% significance levels, respectively.

Table 6. The Phillips curve (occupational - regional level)

	(1)	(2)	(3)	(4)
	Hedonic		Cell median	
	Nominal	Adjusted	Nominal	Adjusted
U	-1.4107***	-1.0640**	-1.6502***	-1.2419**
	(0.3786)	(0.4145)	(0.4842)	(0.5181)
$E(P_{t+12})$		0.1652		0.1917*
		(0.1098)		(0.1112)
Obs.	30,069	30,069	13,380	13,380
R-squared	0.0042	0.0044	0.0166	0.0171

Notes: This table reports results for the baseline Philips curve (Columns 1-3) and the forward-looking Phillips curve (Columns 2-4) at occupational - regional level. The dependent variable in Columns 1-2 is estimated using Model (1) while the dependent variable in Columns 3-4 is calculated using the cell median method. *U* is the monthly unemployment rate at country level. $E(P_{t+12})$ is the 12-month ahead inflation expectation of financial analysts obtained from the NBU Surveys. In all regressions, month of year, occupation, and region fixed effects are included but not reported. Standard errors clustered by month are reported in parentheses. *, **, and *** denote significance at 10%, 5%, and 1% significance levels, respectively.

Table 7. The wage curve

	(1)	(2)	(3)	(4)	(5)	(6)
	$U = U^{rate}$			$U = U^{unemployed}$		
	Panel A. Nominal wage					
lnU	-0.2490***	-0.2784***	-0.9251***	-0.2767***	-0.3041***	-1.0829***
	(0.0563)	(0.0579)	(0.2970)	(0.0614)	(0.0635)	(0.3368)
lnJobs	0.1572***	0.1377***	0.1473***	0.1486***	0.1318***	0.1374***
	(0.0304)	(0.0287)	(0.0286)	(0.0398)	(0.0394)	(0.0289)
words	0.3687***	0.3686***	0.3679***	0.3688***	0.3689***	0.3699***
	(0.0874)	(0.0874)	(0.0880)	(0.0949)	(0.0949)	(0.0881)
$words^2$	-0.0268***	-0.0268***	-0.0269***	-0.0271**	-0.0272**	-0.0277***
	(0.0096)	(0.0096)	(0.0098)	(0.0104)	(0.0104)	(0.0099)
sentences	-0.0962***	-0.0963***	-0.0966***	-0.0971***	-0.0972***	-0.0979***
	(0.0184)	(0.0185)	(0.0186)	(0.0192)	(0.0192)	(0.0182)
slack		-0.0356***			-0.0303***	
		(0.0098)			(0.0095)	
Observations	1,044,363	1,044,363	1,044,363	1,088,555	1,088,555	1,088,555
R-squared	0.4143	0.4149	0.0341	0.4220	0.4224	0.0289
LM test			0.0034			0.0063
F-stat			12.5896			11.0357
	Panel B. Real wage					
lnU	-0.2039***	-0.2325***	-0.6399**	-0.2188***	-0.2458***	-0.7871***
	(0.0508)	(0.0534)	(0.2400)	(0.0538)	(0.0565)	(0.2752)
lnJobs	0.1580***	0.1390***	0.1516***	0.1498***	0.1334***	0.1419***
	(0.0387)	(0.0382)	(0.0280)	(0.0389)	(0.0385)	(0.0283)
words	0.3708***	0.3708***	0.3704***	0.3708***	0.3709***	0.3716***
	(0.0966)	(0.0964)	(0.0886)	(0.0956)	(0.0956)	(0.0885)
$words^2$	-0.0276**	-0.0276**	-0.0277***	-0.0278**	-0.0279**	-0.0283***
	(0.0105)	(0.0105)	(0.0099)	(0.0105)	(0.0105)	(0.0100)
sentences	-0.0971***	-0.0973***	-0.0974***	-0.0978***	-0.0980***	-0.0984***
	(0.0196)	(0.0196)	(0.0185)	(0.0191)	(0.0191)	(0.0181)
slack		-0.0348***			-0.0297***	
		(0.0099)			(0.0097)	
Observations	1,044,363	1,044,363	1,044,363	1,088,555	1,088,555	1,088,555
R-squared	0.3161	0.3168	0.0391	0.3192	0.3197	0.0348

LM test			0.0034			0.0063
F-stat			12.5896			11.0357
Estimator	FE	FE	IV	FE	FE	IV

Notes: This table presents results for the wage curve for full sample. The dependent variable is the natural log of offered wage. *lnU* is (i) the natural log of monthly unemployment rate (Columns 1-3) or (ii) the natural log of the number of unemployed people (Columns 4-6) at country level. Panel A reports results for nominal wage while Panel B reports results for real wage. Columns (3) and (6) are estimated using the instrumental variable estimator while other columns are estimated using the fixed effect estimator. The natural log of one plus the number of vacancies to work abroad (*abroad jobs*) is used as the instrument. *lnJobs* is the natural log of one plus the number of vacancies (excluding aboard jobs). *words* is the natural log of one plus the number of words in the job description. *sentences* is the natural log of one plus the number of sentences in the job description. *slack* is the ratio of one plus the number of job seekers to one plus the number of vacancies. In all regressions, month of year, year, day of week, category, and region fixed effects are included but not reported. Standard errors clustered by month are reported in parentheses. *, **, and *** denote significance at 10%, 5%, and 1% significance levels, respectively.

Table 8. The wage curve with wage dynamic (occupational – regional level)

	(1)	(2)	(3)	(4)
	$U=U^{rate}$		U=Unemployed	
	Nominal	Real	Nominal	Real
	Panel A. FE estimator			
lnW_{t-1}	0.3546***	0.3572***	0.3711***	0.3712***
	(0.0384)	(0.0379)	(0.0386)	(0.0377)
lnU	-0.1708***	-0.1444***	-0.1813***	-0.1489***
	(0.0337)	(0.0298)	(0.0392)	(0.0334)
lnJobs	0.0557***	0.0599***	0.0520***	0.0564***
	(0.0123)	(0.0125)	(0.0113)	(0.0115)
words	0.5112***	0.4233***	0.4784***	0.4007**
	(0.1491)	(0.1541)	(0.1498)	(0.1548)
$words^2$	-0.0534***	-0.0430**	-0.0504***	-0.0412**
	(0.0180)	(0.0187)	(0.0181)	(0.0188)
sentences	-0.1129***	-0.1154***	-0.1098***	-0.1117***
	(0.0259)	(0.0256)	(0.0258)	(0.0255)
Observations	13,326	13,326	14,017	14,017
R-squared	0.9061	0.8734	0.9086	0.8750
	Panel B. GMM estimator			
lnW_{t-1}	0.2050	0.0231	0.5448***	0.4204
	(0.3885)	(0.5063)	(0.1991)	(0.2970)
lnU	-0.2063**	-0.2097**	-0.1341**	-0.1380**
	(0.0938)	(0.1006)	(0.0557)	(0.0668)
lnJobs	0.0598***	0.0704***	0.0479***	0.0550***
	(0.0120)	(0.0169)	(0.0068)	(0.0099)
words	0.5592***	0.4979***	0.4301***	0.3912***
	(0.1458)	(0.1395)	(0.0793)	(0.0842)
$words^2$	-0.0584***	-0.0502***	-0.0453***	-0.0403***
	(0.0163)	(0.0153)	(0.0096)	(0.0099)
sentences	-0.1212***	-0.1354***	-0.1000***	-0.1088***
	(0.0274)	(0.0349)	(0.0192)	(0.0235)
Observations	12,506	12,506	13,194	13,194
AR(2) test	0.5787	0.9590	0.0097	0.1599
Hansen test	0.9098	0.8880	0.2507	0.3643

Notes: This table presents results for the wage curve with the autoregressive term of the dependent variable. *lnU* is (i) the natural log of monthly unemployment rate (Columns 1-2) or (ii) the natural log of the number of unemployed people (Columns 3-4) at country level. The fixed effect estimator is employed in Panel A while in Panel B the GMM estimator is used (lags 2-4 of the log of wage are used as instruments). All regressions are estimated using the cell mean method in which each cell is a pair of occupation – region - month. The dependent variable is the natural log of the cell's average posted wage. *lnJobs* is the natural log of one plus the number of vacancies (excluding aboard jobs). *words* is the natural log of one plus the number of words in the job description. *sentences* is the natural log of one plus the number of sentences in the job description. In all regressions, month of year, year, and occupation – region fixed effects are included but not reported. In the fixed effect estimations, standard errors clustered by month are reported in parentheses while in the GMM estimations, robust standard errors are reported in parentheses. *, **, and *** denote significance at 10%, 5%, and 1% significance levels, respectively.

Table 9. The wage curve (skill heterogeneity)

	(1)	(2)	(3)	(4)
	Aggregate unemployment		Skill-specific unemployment	
	Low skill	High skill	Low skill	High skill
	Panel A. Nominal wage			
lnU	-0.2340***	-0.1933***	-0.1190***	-0.0968***
	(0.0466)	(0.0338)	(0.0166)	(0.0307)
lnJobs	0.1389***	0.0572***	0.0786***	0.0185***
	(0.0292)	(0.0177)	(0.0081)	(0.0062)
word	0.3554***	0.1644***	-0.0003	-0.1045***
	(0.0808)	(0.0602)	(0.0181)	(0.0220)
$word^2$	-0.0277***	-0.0046	0.0132***	0.0269***
	(0.0090)	(0.0070)	(0.0024)	(0.0029)
sentence	-0.0900***	-0.0667***	-0.0391***	-0.0354***
	(0.0161)	(0.0086)	(0.0065)	(0.0057)
Observations	805,538	96,950	391,970	47,122
R-squared	0.4500	0.4688	0.3590	0.3029
	Panel B. Real wage			
lnU	-0.1894***	-0.1490***	-0.1216***	-0.0801**
	(0.0417)	(0.0301)	(0.0167)	(0.0370)
lnJobs	0.1401***	0.0587***	0.0769***	0.0177***
	(0.0283)	(0.0172)	(0.0080)	(0.0063)
word	0.3579***	0.1620**	0.0001	-0.1082***
	(0.0817)	(0.0614)	(0.0184)	(0.0219)
$word^2$	-0.0285***	-0.0048	0.0130***	0.0271***
	(0.0091)	(0.0072)	(0.0024)	(0.0029)
sentence	-0.0910***	-0.0677***	-0.0400***	-0.0362***
	(0.0160)	(0.0086)	(0.0065)	(0.0057)
Observations	805,538	96,950	391,970	47,122
R-squared	0.3471	0.3363	0.3477	0.2886

Notes: This table presents results for the wage curve for sub-samples of low-skill occupations (Columns 1 and 3) and high-skill occupations (Columns 2 and 4). The list of each occupation types is shown in Appendix Table 5. The dependent variable is the natural log of offered wage. Panel A reports results for nominal wage while Panel B reports results for real wage. In Columns 1-2, *lnU* is the natural log of monthly aggregate unemployment rate while in Columns 3-4, *lnU* is the natural log of monthly skill-specific unemployment rate. *lnJobs* is the natural log of one plus the number of vacancies (excluding aboard jobs). *words* is the natural log of one plus the number of words in the job description. *sentences* is the natural log of one plus the number of sentences in the job description. In all regressions, month of year, year, day of week, category, and region fixed effects are included but not reported. Standard errors clustered by month are reported in parentheses. *, **, and *** denote significance at 10%, 5%, and 1% significance levels, respectively.

Table 10. The wage curve (regional heterogeneity)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Kyiv	West	Central	South-East	Kyiv	West	Central	South-East
	$\mathrm{U} = \mathrm{U}_{\mathrm{r}}^{\mathrm{rate}}$				$\mathrm{U} = \mathrm{Unemployed}_{\mathrm{r}}$			
	Panel A. Nominal wage							
lnU	-0.1064***	-0.1093**	-0.2897**	-0.0596	-0.1526***	-0.1381**	-0.3032**	-0.0514
	(0.0185)	(0.0449)	(0.0952)	(0.0412)	(0.0212)	(0.0422)	(0.0954)	(0.0453)
lnJobs	0.0946***	0.0900***	0.2663***	0.1195**	0.0778***	0.0887***	0.2615***	0.1120*
	(0.0275)	(0.0234)	(0.0448)	(0.0494)	(0.0265)	(0.0236)	(0.0463)	(0.0483)
word	0.2219***	0.3485***	0.5673***	0.3705***	0.2256***	0.3486***	0.5634***	0.3685***
	(0.0559)	(0.0829)	(0.1260)	(0.1010)	(0.0555)	(0.0820)	(0.1256)	(0.1003)
word^2	-0.0116*	-0.0269**	-0.0492**	-0.0262**	-0.0122*	-0.0270**	-0.0489**	-0.0262**
	(0.0062)	(0.0097)	(0.0144)	(0.0110)	(0.0062)	(0.0096)	(0.0144)	(0.0110)
sentence	-0.0755***	-0.0859***	-0.1337**	-0.0996***	-0.0773***	-0.0873***	-0.1346**	-0.0995***
	(0.0136)	(0.0201)	(0.0404)	(0.0159)	(0.0133)	(0.0197)	(0.0398)	(0.0156)
Observations	339,825	109,719	140,374	454,445	355,933	114,261	145,526	472,835
R-squared	0.4501	0.4077	0.3908	0.3767	0.4597	0.4159	0.3933	0.3843
	Panel B. Real wage							
lnU	-0.0865***	-0.0782	-0.2642**	-0.0320	-0.1264***	-0.1033**	-0.2829**	-0.0251
	(0.0169)	(0.0427)	(0.1061)	(0.0508)	(0.0180)	(0.0398)	(0.1047)	(0.0546)
lnJobs	0.1025***	0.0914***	0.2661***	0.1185**	0.0861***	0.0903***	0.2610***	0.1116*
	(0.0255)	(0.0234)	(0.0447)	(0.0487)	(0.0245)	(0.0236)	(0.0461)	(0.0475)
word	0.2219***	0.3513***	0.5718***	0.3719***	0.2258***	0.3513***	0.5679***	0.3699***
	(0.0573)	(0.0833)	(0.1265)	(0.1014)	(0.0568)	(0.0824)	(0.1260)	(0.1005)
word^2	-0.0122*	-0.0276**	-0.0502**	-0.0268**	-0.0128*	-0.0277**	-0.0498**	-0.0267**
	(0.0065)	(0.0097)	(0.0145)	(0.0111)	(0.0065)	(0.0097)	(0.0145)	(0.0110)
sentence	-0.0767***	-0.0865***	-0.1345**	-0.1004***	-0.0783***	-0.0879***	-0.1352**	-0.1000***
	(0.0135)	(0.0201)	(0.0403)	(0.0159)	(0.0132)	(0.0197)	(0.0397)	(0.0155)
Observations	339,825	109,719	140,374	454,445	355,933	114,261	145,526	472,835
R-squared	0.3072	0.3034	0.3331	0.2669	0.3129	0.3068	0.3309	0.2696

Notes: This table presents results for the wage curve for sub-samples of Ukrainian region groups, i.e., Kyiv (Columns 1 and 5), Western regions (Columns 2 and 6), Central regions excluding Kyiv (Columns 3 and 7), and South Eastern regions (Columns 4 and 8). The dependent variable is the natural log of offered wage. Panel A reports results for nominal wage while Panel B reports results for real wage. *lnU* is (i) the natural log of monthly unemployment rate or (ii) the natural log of monthly unemployed at regional level. *lnJobs* is the natural log of one plus the number of vacancies (excluding aboard jobs). *words* is the natural log of one plus the number of words in the job description. *sentences* is the natural log of one plus the number of sentences in the job description. In all regressions, month of year, year, day of week, category, and region fixed effects are included but not reported. In Columns 1 and 5, standard errors clustered by month are reported in parentheses while in all other columns, standard errors clustered by region and month are reported in parentheses. *, **, and *** denote significance at 10%, 5%, and 1% significance levels, respectively.

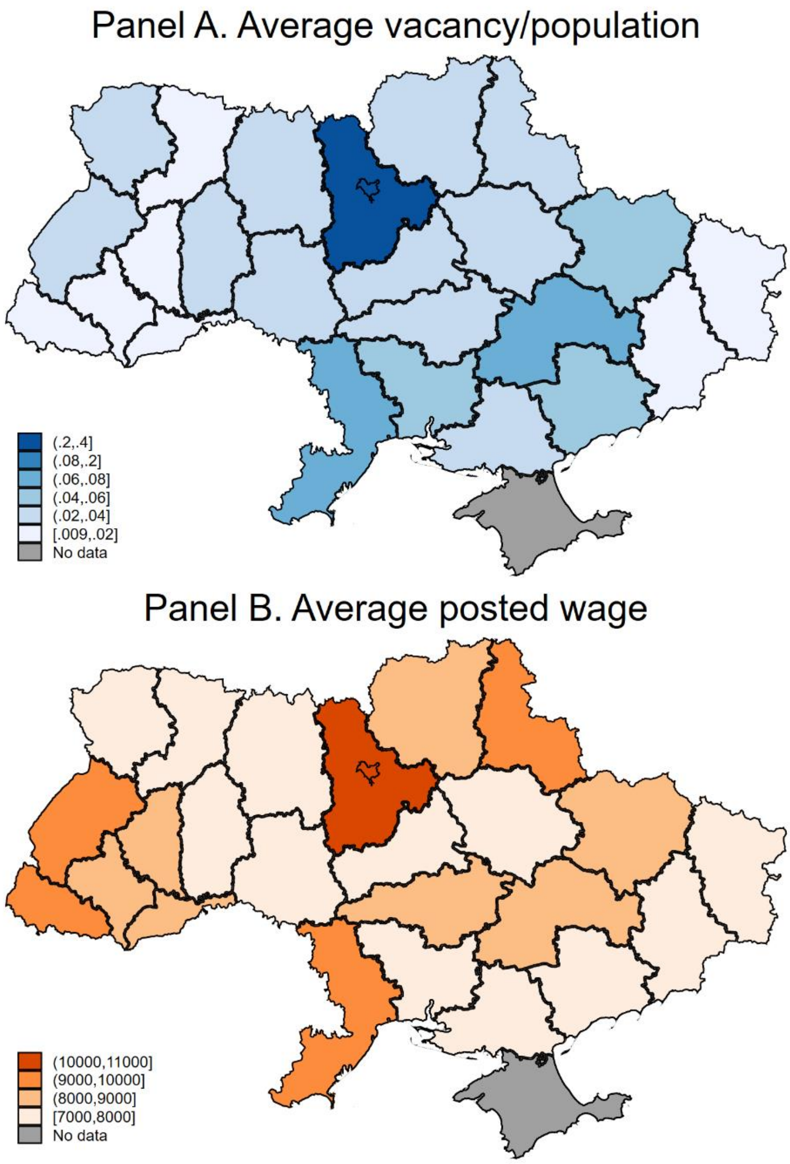
Table 11. The wage curve elasticity before and after visa free regime

	(1)	(2)	(3)	(4)
	lnU=ln(U^{rate})		lnU=ln(Unemployed)	
	Nominal	Real	Nominal	Real
lnU	-0.7485***	-0.6368***	-0.9668***	-0.7094**
	(0.1834)	(0.1752)	(0.3097)	(0.3071)
Visa free	-0.1526***	-0.1610***	-0.8759	-0.7768
	(0.0358)	(0.0348)	(0.7799)	(0.7686)
lnU x Visa free	0.2047**	0.1287	0.1298	0.1091
	(0.0959)	(0.0914)	(0.1365)	(0.1345)
lnJobs	0.1692***	0.1718***	0.1705***	0.1721***
	(0.0293)	(0.0286)	(0.0287)	(0.0283)
words	0.3803***	0.3816***	0.3815***	0.3827***
	(0.0933)	(0.0939)	(0.0939)	(0.0944)
words^2	-0.0285***	-0.0290***	-0.0289***	-0.0293***
	(0.0103)	(0.0105)	(0.0105)	(0.0105)
sentences	-0.0957***	-0.0966***	-0.0964***	-0.0971***
	(0.0201)	(0.0200)	(0.0201)	(0.0201)
Observations	929,590	929,590	929,590	929,590
R-squared	0.3939	0.3084	0.3939	0.3083

Notes: This table presents results for the wage curve for the 2016 – 2019 period. The dependent variable is the natural log of offered wage. Columns 1 and 3 report results for nominal wage while Columns 2 and 4 report results for real wage. *lnU* is (i) the natural log of monthly unemployment rate (Columns 1-2) or (ii) the natural log of the number of unemployed people (Columns 3-4) at country level. *Visa free* is a dummy variable which equals one for the July 2017 – 2019 period and zero otherwise. *lnJobs* is the natural log of one plus the number of vacancies (excluding aboard jobs). *words* is the natural log of one plus the number of words in the job description. *sentences* is the natural log of one plus the number of sentences in the job description. *slack* is the ratio of one plus the number of job seekers to one plus the number of vacancies. In all regressions, month of year, year, day of week, category, and region fixed effects are included but not reported. Standard errors clustered by month are reported in parentheses. *, **, and *** denote significance at 10%, 5%, and 1% significance levels, respectively.

Figures

Figure 1. Average vacancy per population and average salaries by region

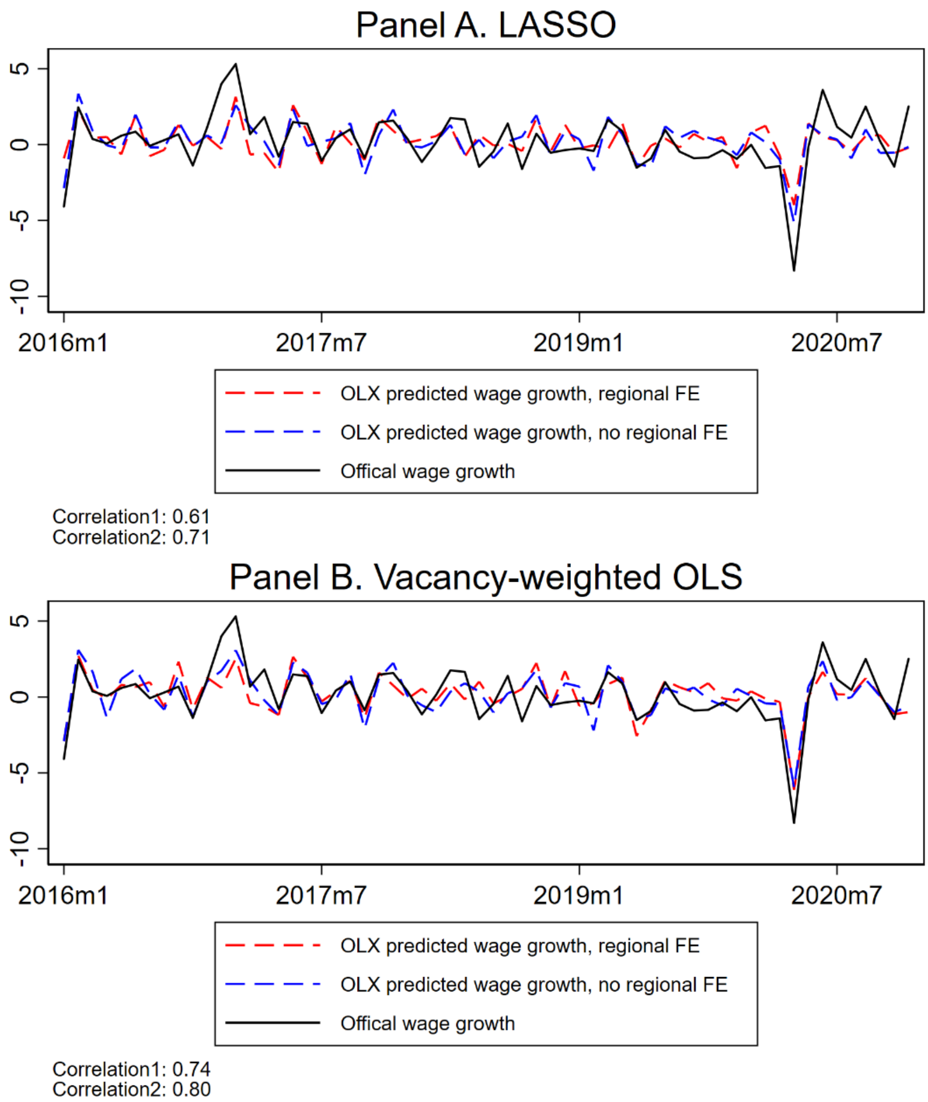


Notes: This figure shows the average monthly vacancy/population ratio and the average monthly offered wage by regions of Ukraine (Panels A and B, respectively). The darker colour means the higher number of vacancies per population/higher average offered wage. The grey area represents Crimea which is the occupied region and is not included in the analysis.

Figure 2. Unemployment statistics

Notes: This figure shows the time series of the official unemployment rate (the solid grey line) and the imputed unemployment rate (the dashed black line) over the 2006 – 2020 period. All series are seasonally adjusted.

Figure 3. Official and online OLX wage indices



Notes: This figure shows the correlation between predicted wage growth using OLX-based categorical wage index and the official wage growth. All series are seasonally adjusted. The solid black line, the dashed red line, and the dashed blue line represent the official growth, the predicted growth using net-of-regional fixed effects wage index, and the predicted growth using no-regional fix-effects wage index, respectively. Correlation 1 is the correlation score between the first and second growth indices while Correlation 2 is the correlation score between the first and third growth indices. In Panel A, the predicted growth indices are obtained from the LASSO approach. In Panel B, the predicted growth indices are obtained from the vacancy weighted approach.

Appendix

Appendix Table 1. Number of vacancies and average salaries by region

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
		Vacancies			Salary		
	Total	Share	Mean	P25	P50	P75	SD
Kyiv	355933	32.70%	10426	5650	9000	13500	6506
Dnipropetrovsk	117760	10.82%	8433	4000	6800	11000	5950
Odesa	104803	9.63%	9339	5000	8000	12000	5781
Kharkiv	87312	8.02%	8337	4500	7000	10250	5387
Zaporizhzhya	53377	4.90%	7293	3750	6000	9000	5233
Donetsk	43595	4.00%	7593	3500	5800	10000	6041
Lviv	33394	3.07%	9104	5000	7750	11111	6251
Poltava	31753	2.92%	7939	4000	6000	10000	5770
Mykolayiv	29303	2.69%	7727	4000	6000	10000	5718
Kherson	24375	2.24%	7766	4000	6000	10000	5790
Vinnytsya	22014	2.02%	8087	4000	6250	10000	6047
Cherkasy	21955	2.02%	7699	3500	6000	10000	5879
Chernihiv	20738	1.91%	8377	4000	6000	10500	6424
Zhytomyr	19491	1.79%	7850	4000	6000	10000	5684
Khmelnytskiy	17688	1.62%	7668	4000	6000	10000	5535
Sumy	17392	1.60%	9630	4000	7000	14500	7267
Rivne	13185	1.21%	7661	3500	6000	10000	6083
Volyn	13056	1.20%	7858	3750	6000	10000	6208
Luhansk	12310	1.13%	7521	3000	5000	10000	6614
Kirovohrad	12183	1.12%	8457	3750	6200	11000	6486
Ivano-Frankivsk	12069	1.11%	8360	4000	6500	10000	6476
Zakarpattya	8890	0.82%	9192	4500	7500	11500	6902
Chernivtsi	8753	0.80%	8649	5000	7500	10500	5667
Ternopil	7226	0.65%	9033	4500	7000	11500	6703

Notes: This table reports statistics on salary (in UAH) and number of vacancies by region. Column 1 shows the total number of vacancies. Column 2 shows the share of the regional vacancies in total vacancies. Columns 3-6 show the average, 25th percentile, median, and 75th percentile offered wages, respectively. Column 7 shows the standard deviation of offered wage.

Appendix Table 2. The forward-looking Phillips curve at country level with different inflation expectation indicators

	(1)	(2)	(3)
	CPI Inflation	Official Wage Inflation	OLX Wage Inflation
	Panel A. Households		
U	-0.2849	-1.8513	-1.2572**
	(0.2488)	(2.4450)	(0.5123)
$E(P_{t+12})$	0.0640	-0.1687	0.0494
	(0.0409)	(0.3811)	(0.1694)
Obs.	57	57	57
R-squared	0.1477	0.0129	0.0500
	Panel B. Business		
U	-0.4527**	-1.2136	-1.3255**
	(0.1981)	(1.8535)	(0.5677)
$E(P_{t+12})$	0.0404	-0.0224	0.0575
	(0.0329)	(0.2430)	(0.0885)
Obs.	57	57	57
R-squared	0.1368	0.0069	0.0542
	Panel C. Banks		
U	-0.4274**	-1.1730	-1.1627**
	(0.2104)	(1.9777)	(0.5672)
$E(P_{t+12})$	0.0589	-0.0057	0.1466
	(0.0564)	(0.3812)	(0.1262)
Obs.	57	57	57
R-squared	0.1264	0.0066	0.0634

Notes: This table reports results for the forward-looking Phillips curve at country level. The dependent variable is the inflation rate measured by i) the monthly official CPI (Column 1), ii) the monthly official wage growth (Column 2), and iii) the country-level OLX wage growth obtained from estimating Model (1) (Column 3). *U* is the monthly unemployment rate at country level. $E(P_{t+12})$ is the 12-month ahead inflation expectation of financial analysts obtained from the NBU Surveys. Panels A, B, and C show results for the inflation expectations of households, business, and banks, respectively. Robust standard errors are reported in parentheses. *, **, and *** denote significance at 10%, 5%, and 1% significance levels, respectively.

Appendix Table 3. First stage results

	(1)	(2)
	U=U^{rate}	U=Unemployed
abroad jobs	-0.0308***	-0.0308***
	(0.0087)	(0.0093)
lnJobs	-0.0061	-0.0059
	(0.0088)	(0.0082)
words	-0.0042	-0.0017
	(0.0027)	(0.0028)
$words^2$	0.0008	0.0002
	(0.0007)	(0.0007)
sentences	0.0005	0.0001
	(0.0009)	(0.0011)
Obs.	1,044,363	1,088,555
R-squared	0.8905	0.8287

Notes: This table presents the results for the first stage. The dependent variable is the natural log of monthly unemployment rate (Column 1) or the natural log of number of unemployed people (Column 2) at country level. *abroad jobs* is the natural log of one plus the number of vacancies (excluding aboard jobs) to work abroad. *lnJobs* is the natural log of one plus the number of vacancies (excluding aboard jobs) (excluding aboard jobs). *words* is the natural log of one plus the number of words in the job description. *sentences* is the natural log of one plus the number of sentences in the job description. In all regressions, month of year, year, day of week, category, and region fixed effects are included but not reported. Standard errors clustered by month are reported in parentheses. *, **, and *** denote significance at 10%, 5%, and 1% significance levels, respectively.

Appendix Table 4. The wage curve – additional instrument

	(1)	(2)	(3)	(4)
	Nominal	Real	Nominal	Real
	U=U^{rate}		U=Unemployed	
lnU	-0.6931***	-0.4912***	-0.8557***	-0.6380***
	(0.2126)	(0.1811)	(0.2528)	(0.2122)
lnJobs	0.1507***	0.1538***	0.1405***	0.1440***
	(0.0291)	(0.0284)	(0.0294)	(0.0286)
word	0.3682***	0.3705***	0.3696***	0.3714***
	(0.0877)	(0.0885)	(0.0878)	(0.0884)
$word^2$	-0.0269***	-0.0276***	-0.0276***	-0.0282***
	(0.0097)	(0.0099)	(0.0099)	(0.0100)
sentences	-0.0965***	-0.0973***	-0.0976***	-0.0982***
	(0.0185)	(0.0184)	(0.0182)	(0.0181)
Observations	1,044,363	1,044,363	1,088,555	1,088,555
R-squared	0.0402	0.0416	0.0359	0.0381
Sargan-Hansen test	0.0663	0.1956	0.1026	0.2354
LM test	0.0081	0.0081	0.0169	0.0169
F-stat	6.9136	6.9136	6.482	6.482

Notes: This table presents results for the wage curve. The dependent variable is the natural log of offered wage. Columns 1 and 3 report results for nominal wage while Columns 2 and 4 report results for real wage. *lnU* is (i) the natural log of monthly unemployment rate (Columns 1-2) or (ii) the natural log of monthly unemployed (Columns 3-4) at country level. *lnJobs* is the natural log of one plus the number of vacancies (excluding aboard jobs) (excluding abroad jobs). *words* is the natural log of one plus the number of words in the job description. *sentences* is the natural log of one plus the number of sentences in the job description. *supply* is the ratio of one plus the number of job seekers to one plus the number of vacancies. All regressions are estimated using the instrumental variable estimator where abroad jobs and abroad seekers are the instruments. *abroad jobs* is the natural log of one plus the number of vacancies (excluding aboard jobs) to work abroad. *abroad seekers* is the natural log of one plus the number of job seekers who look for aboard jobs. In all regressions, month of year, year, day of week, category, and region fixed effects are included but not reported. Standard errors clustered by month are reported in parentheses. *, **, and *** denote significance at 10%, 5%, and 1% significance levels, respectively.

Appendix Table 5. List of high-skill and low-skill occupations

High-skill occupations	Low-skill occupations
Accountant, Administrator, Agronomist, Analyst, Auditor, Dentist, Developer, Director, Doctor, Ecologist, Economist, Educator, Electrician, Engineer, Governess, HR, IT Specialist, Leader, Manager. Mathematician, Pharmacist, Programmer, Researcher, Scientist, Supervisor, Teacher	All other occupations, e.g., Driver, Bartender

Notes: This table shows the list of job titles belonging to high-skill and low-skill occupations.