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Wage Setting and Unemployment: Evidence from Online Job Vacancy Data

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Abstract

This paper examines the relationship between labour market conditions and wage dynamics by exploiting a unique dataset of 0.8 million online job vacancies. We find a weak trade-off between aggregated national-level wage inflation and unemployment. This link becomes more evident when wage inflation is disaggregated at sectoral and occupational levels. Using exogenous variations in local market unemployment as the main identification strategy, a negative correlation between vacancy-level wage and unemployment is also established. The correlation magnitude, however, is different across regions and skill segments. Our findings suggest the importance of micro data's unique dimensions in examining wage setting – unemployment relationship.

Keywords: Phillips curve, wage curve, heterogeneity, micro data, online vacancies.

JEL codes: C55, E24, E31, E32.

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Abstract

This paper examines the relationship between labour market conditions and wage dynamics by exploiting a unique dataset of 0.8 million online job vacancies. We find a weak trade-off between aggregated national-level wage inflation and unemployment. This link becomes more evident when wage inflation is disaggregated at sectoral and occupational levels. Using exogenous shock to local market unemployment as the main identification strategy, a negative correlation between vacancy-level wage and unemployment is also established. The correlation magnitude, however, is different across regions and skill segments. Our findings suggest the importance of micro data's unique dimensions in examining wage setting – unemployment relationship.

"*Probably the single most important macroeconomic relationship is the Phillips Curve … (which) define the feasible set for monetary policy and thus play a decisive role in its formulation.*"

George A. Akerlof

Nobel Prize Lecture, December 8, 2001

1 Introduction

For decades the Phillips curve, the relationship between inflation and unemployment, has been used as guidance for 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 Phillips curve in advanced economies (e.g., Beaudry and Doyle 2000, Roberts 2006), while some others show that the curve is well alive after accounting for other factors such as inflation expectations or sectoral heterogeneity (e.g., Imbs, Jondeau, and Pelgrin 2011, Coibion and Gorodnichenko 2015, Moretti, Onorante, and Zakipour-Saber 2019). Contributing to the debate is the development of the wage curve, which suggests a negative correlation between level of wages and local unemployment. However, the wage curve has been also subjected to critics 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 setting and labour market conditions.

In this study, we attempt to shed light into 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 Job Category on OLX.ua, a leading Ukrainian online advertisement platform. The data coverage is comprehensive with about 0.8 million job vacancies of 23 broadly defined categories posted daily over the 2016-2019 period in all regions of Ukraine. This rich dataset allows us to capture the countrywide labour market conditions more precisely. At the same time, various job dimensions contained in the dataset are 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 can be a good approximation of official statistics on the country-level wage growth. The examination of the Phillips curve is then done at multiple levels of wage inflation i.e. country, sectoral, and occupational levels. We find that at the national level, the curve slope 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. Next, we 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. Additional investigation indicates 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 main fundamentals for many macroeconomic theories, its disappearance has been of concern to economists and policymakers. This flattening could be explained by the “anchored expectations” hypothesis (see, e.g., Bernanke 2010, Blanchard 2016, Hooper, Mishkin, and Sufi 2019). More specifically, if inflation expectations have become anchored due to the increasing creditability of modern central banks, inflation will become much less sensitive to business cycles. Alternative explanation is the downward nominal wage rigidity due to workers' bargaining power (e.g., Ball and Mazumder 2011, Daly and Hobijn 2014). There is also evidence that long-term unemployment is less likely to have influence on inflation because of its detachment from the labour market (Llaudes 2005, Gordon 2013, Krueger, Cramer, and Cho 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 sources of variations in wage dynamics (Kudlyak 2015). For example, the micro 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 (see, e.g., Shin 1994, Carneiro, Guimarães, and Portugal 2012, Kudlyak 2014, Daly and Hobijn 2017). Wage cyclicity also varies across income distribution groups, demographic groups, and other structural characteristics (Solon, Barsky, and Parker 1994, Devereux and Hart 2006, Martins 2007, Cervini-Plá, López-Villavicencio, and Silva 2018, Dapi 2019). 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 capture the important heterogeneity that cannot be observed in the macro-based analyses. The contribution of this study is that our Phillips curve examination is drawn on a rich micro-level dataset. In doing so, 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 is subjected to several criticisms.[2] Some of 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 might exist as the level of wages might also affect the unemployment level. In addition, the estimates of the wage curve's slope might be sensitive to the choice of dependent variable's measures. For example, using earnings as a payment indicator might lead to bias as an increase in earnings can be attributed to either higher wage or higher number of hours worked.[3]

The dataset of online job vacancies, coupled with the recent developments in the Ukrainian labour market, allow us to address these criticisms. First, we deal with the endogeneity bias by taking advantages of the growing opportunities for Ukrainian workers to work abroad as a source of exogenous variation in an instrumental variable framework. With an increase in the number of vacancies to work abroad, one would expect a decrease in the level of the home markets' unemployment due to the outflows of local workers. At the same time, local firms are less likely to adjust their wage offers as a direct response to the increase of working abroad offers. Instead, the change in the wage setting behaviours is rather influenced by the change in domestic labour market conditions. Second, using our unique data, we can control for labour supply at the finely

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

disaggregated levels e.g. sector – region in the wage curve estimation. Thus, any significant estimates of unemployment after controlling for the local labour supply would indicate the existence of wage-setting curve.

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 the textual analytics and machine learning techniques to extract important information e.g. skill requirements from the job descriptions'/advertisements' text (see, e.g., Boselli et al. 2017, Dadzie et al. 2018, Deming and Kahn 2018, Djumalieva, Lima, and Sleeman 2018). The extracted information is then employed for the analysis of trends in skill demand or market segmentation (Hershbein and Kahn 2017, Turrell et al. 2018).

Other studies use online vacancy data to examine the changes in aggregate labour markets and create labour market indices. For instance, online data have been used to measure skill mismatch, labour supply/demand, or labour market concentration/tightness. Subsequently, these indices can be employed to investigate the employment effects of minimum wages or to predict wages, rate of mismatch unemployment, expected unemployment duration, and migration patterns (Azar et al. 2018, Adrjan and Lydon 2019, Bessen et al. 2019, Mamertino and Sinclair 2019, Turrell et al. 2019). 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 dataset employed for the analysis. In Section 3, we discuss our empirical strategies and results. Section 4 concludes and provides implications.

2 Data and sample

2.1 Online vacancy data

Data used in this study are from OLX.ua, which is one of the leading online advertisement platforms in Ukraine. 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 in exploring the link between wage setting and unemployment. Moreover, OLX.ua also provides us with data on job seekers, which is beneficial to our instrumental variable framework.

Our data cleaning process is as follows. First, since data coverage for the pre-2016 period is limited, we only keep data covering the 01/2016 – 06/2019 period for analysis. Second, we keep vacancies which i) are full-time jobs, ii) offer monthly salary, and iii) have wages listed in Hryvnia (UAH). Third, all listed wages which are lower 1,000 UAH are excluded. Salaries are then trimmed at the 0.5 and 99.5 percentiles by region and by category. Finally, we exclude from the final sample all jobs listed in Crimea or jobs of which OLX category is “Early careers/Students” or “Work abroad”. After cleaning, our dataset contains more than 0.8 million vacancies belonging to 23 job categories.

Table 1 reports the overview of salaries in our sample. Over the 2016 -2019 period, we observe an increase in the average salary that is generally in line with the trend reported by the State Statistics Office. More specifically, the average monthly salaries of

7,451 UAH (311 USD) and 9,260 UAH (387 USD) in 2017 and 2018 in our sample are relatively similar to the official statistics (7,104 UAH and 8,865 UAH, respectively). One exception is the average salary in 2016 when the sample's statistics is significantly higher than the official one (6,978 UAH vs. 5,183 UAH). Nevertheless, this basic comparison suggests that online vacancy data could be generally representative of the aggregate labour market. In fact, if anything, online data could contain more information that is not observable in data collected through the traditional methods. For example, our online vacancy data show that the upward trend in salaries is not limited to the high-paid segments but occurs across wage distribution. In other words, the increase in average salaries is not driven only by the increase in the salaries of high-paid occupations. At the same time, there is also a decline in the wage dispersion over the 2016 – 2019 period.

Figure 1 illustrates the statistics on regional salaries and vacancies.[4] As can be seen, top 4 regions which offer more than 50,000 jobs over the examined period include Kyiv (both capital and region), Dnipropetrovsk, Odesa, and Kharkiv. This is not surprising since these regions are either large in terms of size or the country's industrial, service, and financial centres. However, regions with more vacancies do not necessarily offer the highest average salary (except from Kyiv). Taking into account both salary's mean and median, it appears that salaries in Kyiv are relatively higher than the ones in other regions. In contrast, some regions like Sumy or Zakarpattya, despite having the highest average salaries, experience the largest wage dispersions. The average salaries in some other regions such as Donetsk, Luhansk, or Zaporizhzhya are considerably lower than the country's 2016-2018 official average of around 7,000 UAH. This could be

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

because these regions are in (or close to) the zone of military conflict which has had negative effects on the affected regions' economies and labour markets.

Table 2 presents more statistics by job categories. Job categories offering the highest number of vacancies are Retail/Sales/Purchases, Transportation/Logistics, Construction, Bars/Restaurants, 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 the neighbouring countries e.g. Poland. Yet again, more job offers do not come with higher salaries. The average salaries offered in the Retail/Sales/Purchases and Bars/Restaurants categories are in fact at the bottom of the average wage distribution. Oppositely, vacancies in the Transportation/Logistics, Construction, and Production/Energy categories offer the highest salaries. This difference could be because of the composition of jobs contained in each category. More specifically, the most requested job titles in our sample belong to the Retail/Sales/Purchases and Bars/Restaurants categories but these occupations' offered salaries are relatively low (Table 3). In other words, the Retail/Sales/Purchases and Bars/Restaurants categories are dominated by low-paid jobs, leading to the categories' overall low salary.

2.2 Online wage index vs. official statistics

To construct the wage inflation indices from online vacancy data, we employ a two-month rolling-window hedonic wage model of the following form:

$$W_{it} = \alpha + \beta Month_t + \ FEs + \varepsilon_{it} \quad (1)$$

where W_{it} is the natural log of offered wage for vacancy i posted on date t. $Month$ is a dummy variable, which equals 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 can be considered as the net-of-fixed effects measures of wage growth.

We first estimate model (1) for all vacancies to get 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:

$$\Delta \mathrm{W}_{m}^{official} = \alpha + \Delta \mathrm{W}_{cm}^{OLX} \beta + \varepsilon_{m} \tag{2}$$

where $\Delta W_{m}^{official}$ is the monthly wage growth reported by the statistics office. ΔW_{cm}^{OLX} is a vector of monthly wage inflation by category obtained from model (1) i.e. the estimated β.

Model (2) is estimated using two approaches. In the first approach, we adopt the least absolute shrinkage and selection operator (LASSO), a machine learning method, 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 of 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 (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.[5]

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

$$\Delta \mathrm{W}_{cm}^{weighted\ OLX} = \frac{Vacancies_{cm}}{Total\ vacancies_{m}} \times \Delta \mathrm{W}_{cm}^{OLX} \tag{3}$$

The correlation between the predicted country-level wage inflation index obtained from model (2) and the official statistics is shown in Figure 2. As can be seen, the online-based wage index is closely matched with the official wage index with the correlation of 65-80%. This reasonably high correlation suggests that (i) the online vacancy data can be representative of the labour market and (ii) these data can be exploited for wage inflation nowcasting.

We also check the predictive power of our data in predicting the official unemployment employing a simple linear regression as follows:

$$U_m = \alpha + \beta Employment_{cm}^{OLX} + \varepsilon_m \tag{4}$$

where U_m is the monthly official unemployment rate. $Employment_{cm}^{OLX}$ is the OLX market indicators at the category level. Here we use two measures of online labour market indicators including i) the change in the number of vacancies for each category and ii) the change in the number of job seekers for each category. Figure 3 plots the correlation between the predicted unemployment rate obtained from model (4) and the official rate.

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

The results reveal a weak predictive power of the online labour market indicators in predicting the official unemployment rate.

3 Empirical analysis

3.1 The Phillips curve

3.1.1 The Phillips curve at the country level

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

$$\Delta P_m = \alpha + \beta U_m + Controls_{m-1}\delta + Month\ of\ year\ FE + \varepsilon_m \tag{5}$$

where ΔP_m is either i) the monthly official CPI, ii) the monthly official wage growth, and iii) the estimated monthly wage growth obtained from estimating model (1). Model (5) is estimated for both nominal and inflation expectation-adjusted inflation measures. U_m is the official unemployment rate. $Controls_{m-1}$ is a vector of control variables including the i) lagged inflation (ΔP_{m-1}) and ii) change in UAH/USD exchange rate ($\Delta UAH/USD_{m-1}$).[6] We also control for month of year fixed effects.

Results reported in Table 4 show that the Phillips curve estimated for nominal Headline CPI inflation is hardly observed. That is, the coefficient for unemployment, i.e., the slope of the Phillips curve, is negative but statistically insignificant. After controlling for inflation expectations, the slope of the Phillips curve becomes more pronounced: a one percent increase in unemployment reduces wage inflation by 0.03 percent. However, there is no evidence of the Phillips curve for the official wage inflation regardless of whether inflation expectations are controlled for. In contrast, there is a negative

[6] The inclusion of exchange rate is motivated by the evidence that the pass-through effect of exchange rate to domestic inflation in Ukraine is higher compared to other studies, see Faryna (2016).

relationship between unemployment and the online-based wage inflation index, although the effect is weakly significant. Our results are robust to different measures of inflation expectations. In fact, the effect of unemployment on inflation is strongest (both in terms of the statistical and economic significances) when the businesses' or banks' forecasts are used (Appendix Table 2).

Overall, the findings confirm our previous statements about the similarity between online vacancy wage index and the official statistics. The results also indicate that nominal wage cyclicity at the aggregate level is seemingly flat, which is consistent with what observed in advanced economies (Cunningham, Rai, and Hess 2019, Kiss and Van Herck 2019). Furthermore, the stronger slopes after accounting for inflation expectation are in support of the recent studies which suggest the importance of expectation-augmented Phillips curve (see, e.g., Coibion and Gorodnichenko 2015, Jorgensen and Lansing 2019, Moretti et al. 2019).

3.1.2 The Phillips curve at the disaggregated levels

In this section, we use disaggregated data to investigate the inflation – unemployment relationship. More 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 2.2. 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 has at least ten observations.

Consistently with the previous results, the Phillips curve is only observed when inflation expectations are adjusted for. Moreover, the slope of the curve becomes steeper with the higher levels of disaggregation. Particularly, accounting for the sectoral (categorical) heterogeneity, an increase of one percent in unemployment rate is related to a 0.08 percent decrease in wage growth. This figure is slightly higher i.e. about 0.1 percent when we control for the occupational heterogeneity. 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 (e.g., Imbs et al. 2011, Byrne, Kontonikas, and Montagnoli 2013, Fitzgerald and Nicolini 2014, Hooper et al. 2019). In other words, these results confirm the importance of heterogeneity in the examination of the Phillips curve.

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.

$$lnW_{im} = \alpha + \beta U_m + Controls_{im}\delta + FEs + \varepsilon_{im} \tag{6}$$

where *lnW* is the natural log of wage offered in vacancy *i* posted in month *m*. *U* is the natural log of the country-level unemployment rate in month *m*. *Controls* is a vector of vacancy-level control variables to account for the quality of job description including 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 description is likely to contain more detailed information and/or requirements that can determine the offered salaries. *FEs* is a vector of various fixed effects i.e. month of year, year, day of week, category, and region.

To address the potential biases e.g. aggregation bias, composition bias, or simultaneity bias, different specifications/identifications of model (6) are employed. More specifically, to address the concern about endogeneity, in addition to the fixed effect (FE) estimation, model (6) is also estimated using instrumental variables (IV) estimation in which U is the endogenous variable. We use the natural log of number of vacancies to work abroad (*abroad jobs*) as the instrument since an increase in the number of working abroad vacancies would directly lead to a negative labour supply shock to domestic labour market.[7] At the same time, domestic firms are unlikely to re-set their wages in direct response to the changes in the employment opportunities (for local workers) in foreign countries.

Since the existing evidence of the wage curve relies on data on individual salaries, there is a concern about the 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 in our setup since we use data on wages offered by firms. Thus, other factors that could affect wage setting but are not vacancy-specific e.g. technological development of the industry could be captured by time, regional, and industrial fixed effects.

The existing literature has also casted doubt on the validity of the wage curve i.e. whether it is just a mis-specified labour supply curve and/or a mis-specified Phillips curve. To address this concern, we add in model (6) an indicator of monthly labour supply

[7] The instrument is measured at the region-month level.

for a given job category (*s*) – region (*r*) pair (*supply*). It is measured as the ratio of one plus the number of job seekers to one plus the number of vacancies. If the unemployment rate is simply a mis-measured labour supply indicator, then the estimated coefficient on *U* should be less (if not) statistically significant with this inclusion.

Further, 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 unemployment variable is also treated as endogenous and the modified model (6) is estimated using (1) the 2SLS estimator and (2) the first difference-GMM dynamic panel estimator.

In addition to country-level measure of unemployment, we also measure unemployment at regional level i.e. the natural log of the number of unemployed people in a region ($U^{unemployed}$). Finally, we estimate model (6) using both nominal wage and real wage to account for the business cycle variation in local prices.

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

Table 7 provides firm evidence of the wage curve: the estimated coefficients on unemployment are negatively significant in all regressions. However, there are differences in the magnitude. In cases of FE estimator and country-level unemployment (Column 1), if unemployment rate increases by a one percentage point, offered salaries decline by 0.8-0.9 percentage points. The effect becomes two times larger when we use IV estimator: a one percentage point increase in unemployment leads to a reduction of 2.4-2.8 percentage points in wages. We also find statistically significant coefficients on regional unemployment measure. That is, a one percentage point increase in local unemployment is related to declines of 0.2 percentage points in wages for FE estimation and 0.6-0.8 percentage points for IV estimations. It is worth noting that our estimates of unemployment are relatively comparable to those in other European countries e.g. Germany or Spain (Wagner 1994, García-Mainar and Montuenga-Gómez 2003, Montuenga-Gómez, García-Mainar, and Fernandez 2003).

To check the validity of our IV approach, we report the first stage results in Appendix Table 3. As expected, the higher number of abroad jobs has a negative impact on unemployment: more working abroad vacancies provide opportunities to work for individuals who might be otherwise unemployed, leading to the reduction in the home country's unemployment. In a further robustness check, we include the natural log of the number of job seekers who look for abroad jobs as another instrument. Our baseline results are similar with the inclusion of this instrument (Appendix Table 5).

Our analysis of the wage curve adding the lagged log of wage suggests the co-existence of the Phillips curve and the wage curve (Table 8). Regardless of estimators employed, the coefficients on both lagged log of wage and unemployment are statistically significant. 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 0.5-0.68).[8] These results suggest that the wage curve is not the mis-specified Phillips curve

[8] In another strand of literature (e.g., Blanchard and Katz 1997, Dyrstad and Johansen 2000, Bell, Nickell, and Quintini 2002), the two-stage approach instead of cell mean method is used to analyse the wage curve accounting for the lagged log of wage. The common finding is that the estimated coefficients on the autoregressive term are significantly larger than the those reported in the cell mean method and/or closer to one. Our analysis using this approach, however, yields the opposite results: our estimates are between 0.07-0.34, way below the unity and substantially lower than those reported in these studies. Results of this analysis are available upon request.

but rather reflects the negative relationship between wage level and unemployment in which certain degree of wage stickiness exists.

Three main conclusions can be drawn upon the above findings. First, the sharper slope in the IV estimations suggests the importance of controlling for the endogeneity bias in investigating the wage curve. Second, the significant responsiveness of wages to unemployment at both country and regional levels indicates the persistence of the wage curve, regardless of implicit assumption about labour mobility. Third, the existence of the wage curve does not "disapprove" the existence of the Phillips curve. In fact, our results point to the reconciling 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, wages of low-skill jobs are expected to be in the left tail of the wage distribution. Thus, it is less costly for firms to raise wages of low-skill jobs than that of high-skill ones. Further, 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.

The results presented in Table 9 confirm that wages appear to be more cyclical for low-skill jobs compared to high-skill ones.[9] That is, the size of the former's wage curve elasticity is almost three times as large as that of the later in case of nominal wages. The difference is even clearer in case of real wages: only the slope of the wage curve for low-skill occupations is statistically significant. This result is in line with other studies (e.g., Hoynes, Miller, and Schaller 2012, Borjas 2017) which show that labour market outcomes e.g. earnings of low-education workers (low-skilled workers) are more affected by the economic downturns or slack labour markets. The finding also highlights the importance of skill composition in examining the wage setting – 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. The results in Table 10 indicate that wages in Western and Central Ukraine are more procyclical compared to wages in Kyiv and South-East regions. Particularly, a one percentage point rise in the country-level unemployment is correlated to a reduction of nearly four percentage points in wages in the former regions, which is 1-3 times larger than the reduction in the later.

This difference could be explained by the geographical locations/history of these regions as well as the recent political developments. That is, since Western and Central regions share borders with Central and Eastern European countries, they are more prone to short- and long-term emigration of the workforce to the neighbouring countries e.g. Poland. This outflow of Ukrainian workers is likely be enhanced by the economic/geopolitical crisis in 2014-2015. Another factor that contributes to the growth

[9] Borrowing the classifications of jobs by skills used in previous studies (e.g., David and Dorn 2013), we classify jobs that typically do not require college education as low-skill occupations e.g. drivers or security guards and those that require college education as high-skill occupations e.g. economists or programmers.

of emigration is the easing of Polish law on the employment of foreigners in 2014 that facilitates the possibility of staying and seeking jobs in Poland for Ukrainian citizens. Additionally, in 2017, a visa free agreement between Ukraine and Schengen area, which allows the free movement of Ukrainian citizens across Schengen countries, was made. This agreement could also potentially increase the employment opportunities for Ukrainian workers in these countries. In contrast, South-East regions historically had tight linkages with Russia in terms of labour outflows which have been negatively affected by the geopolitical crisis started in 2014.

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 visa affects the elasticity of the wage curve, we incorporate in model (6) the interaction term between unemployment indicator and post-visa regime indicator (*Visa free*). This indicator is a categorical variable, which equals to 0 for the period prior to July 2017 (when the visa free regime came effect); 1 for the July – December 2017 period; 2 for the January – June 2018; and 3 for the July – December 2018 period. It should be noted that the first stage, both unemployment indicator and its interaction with *Visa free* are instrumented on the instrument and the interaction with *Visa free*. We do not include *Visa free* as a covariate since time fixed effects are controlled for.

As can be seen in Table 11, the visa free regime has short-lived and weak effect on the elasticity of the wage curve. More specifically, during six months since the regime took place, nominal wages are less sensitive to unemployment. The effect immediately disappears in the subsequent periods and is not observed for real wages. The lack of sensitivity of the wage curve to the regime can be explained by several facts. First, this regime is not the first policy change that opens opportunities for Ukrainian workers to work abroad. In fact, in May 2014, Polish government had relaxed the legal requirements for Ukrainian citizens to stay and find a job in Poland, which have led to a notable outflow of Ukrainian workers to Poland since. 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 were doubled in 2015 and continue 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, it also comes with certain difficulties related to languages or skill requirements that are not easy to overcome. Taken together, the impact of the 2017 visa free regime could be absorbed by the previous policy change's effects.

4 Conclusions

Recent years have witnessed the continuing debate among economists and policymakers about whether, and the extent to which, the relationship between wage setting and unemployment (still) exists. Both supporting evidence and critics of the two main phenomena about this 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 critics about potential biases that might 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 wage setting – labour market conditions matter, there have been also concerns about the model used to estimate the curve.

Given the importance of the Phillips and wage curves for monetary policymaking, there is a need for a better understanding of the relationship that the curves represent. In this study, we take up this task and exploit the new dataset of online vacancies to perform a rigorous analysis of the curves. More specifically, we utilize the unique features of about 0.8 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 Phillips curve seems to be “flattening”, which is observed in cases of both official inflation measures and online vacancy-based inflation. 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 control for (i) heterogeneity e.g. regional difference or skill composition of the labour market, (ii) misspecification, and (iii) endogeneity bias.

The findings in this study suggest that the link between wage setting and unemployment exists in both short term (the Phillips curve) and longer term (the wage curve). Hence, it is plausible to use economic theories built on this link for policymaking. Nonetheless, it is important to account for potential biases to get the better estimates of the relationship, thus, a better policy. One way of doing so is to take advantage of the new and rich source of labour market data, online vacancies, in the Phillips curve/wage curve analysis. Using this new data source, 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 slowly updated.

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Tables

Table 1. Summary statistics of salary over time

	(1)	(2)	(3)	(4)	(5)
	Mean	P25	P50	P75	SD
Full sample	7,916	4,000	6,000	10,000	5,859
By year					
2016	6,978	3,000	4,750	8,000	6,198
2017	7,451	4,750	6,100	8,500	4,732
2018	9,260	6,000	8,000	11,000	5,078
2019	10,534	7,000	9,500	12,500	5,417
By quarter of year					
Q1	7,268	3,750	6,000	9,200	5,307
Q2	7,657	4,000	6,000	10,000	5,477
Q3	7,919	4,000	6,000	10,000	6,121
Q4	9,076	4,750	7,000	11,754	6,415

Notes: This table shows the summary statistics of salaries (in UAH) in our sample. Columns (1)-(4) show the average, 25^{th} percentile, median, and 75^{th} percentile salaries, respectively. Column (5) shows the standard deviation of salary.

Table 2. Number of vacancies and average salaries by categories

	(1)	(2)	(3)	(4)	(5)	(6)
	Vacancies	Salary				
	Total	Mean	P25	P50	P75	SD
Retail/Sales/Purchases	188,784	6,016	3,700	5,050	7,500	3,356
Transportation/Logistics	99,203	8,955	4,750	7,000	11,000	6,368
Bars/Restaurants	97,195	6,313	3,750	5,500	8,000	3,752
Construction	89,719	11,820	6,000	10,000	15,395	8,026
Others	82,879	10,076	4,500	8,000	15,000	6,879
Production/Energy	67,450	9,603	5,000	8,000	13,004	6,138
Beauty/Fitness/Sports	32,963	5,895	3,000	5,000	7,500	3,894
Services	30,526	6,633	3,050	5,000	8,250	4,967
Security/Safety	25,828	4,652	3,000	4,000	5,880	2,588
Home assistance service	21,147	9,368	4,000	7,000	12,500	7,378
Law and Accounting	9,239	5,911	3,500	5,000	7,500	3,279
Marketing/Advertising/Design	8,662	6,596	4,000	5,500	8,000	4,085
Medicine/Pharmacy	8,354	5,199	2,750	4,000	6,050	3,954
Secretary	8,034	5,490	3,500	4,900	7,000	3,029
IT/Telecom/Computers	7,563	7,326	4,000	5,750	9,000	5,602
Real estate	7,216	11,626	7,000	10,000	15,000	6,902
Tourism/Recreation/Entertainment	7,045	6,666	3,500	5,001	8,000	5,030
Education	6,730	5,034	2,200	3,500	6,000	4,641
Agriculture/Agribusiness/Forestry	2,922	9,065	5,500	8,000	11,000	5,332
HR	1,891	9,189	6,000	8,000	11,000	4,677
Telecommunications/Communication	1,860	8,253	5,500	7,500	10,000	3,989
Culture/Art	1,755	6,976	3,000	5,000	8,500	6,138
Banks/Finance/Insurance	1,700	8,385	5,750	7,500	10,000	3,957

Notes: This table reports statistics on salary (in UAH) and 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 salaries, respectively. Column (6) shows the standard deviation of salary.

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

	(1)	(2)	(3)	(4)	(5)	(6)
	Vacancies	Salary				
	Total	Mean	P25	P50	P75	SD
Seller	63,932	5,106	3,000	4,500	6,500	2,724
Driver	41,200	9,814	5,000	8,000	12,500	6,717
Consultant	27,481	5,683	3,750	5,000	7,000	2,913
Manager	26,332	8,008	4,850	7,000	10,000	4,745
Cook	25,966	7,125	4,350	6,000	9,000	4,130
Security guard	21,289	4,580	3,000	4,000	5,750	2,428
Assistant	19,540	7,009	4,000	5,950	9,000	4,700
Loader	18,738	6,048	4,000	5,250	7,500	3,211
Barman	17,049	5,866	3,750	5,250	7,500	2,965
Handyman	16,632	8,247	4,500	6,500	10,000	5,468

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, 25^{th} percentile, median, and 75^{th} percentile salaries, respectively. Column (6) shows the standard deviation of salary.

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	-0.0064	-0.0318**	0.0584	-0.0075	-0.0048	-0.0745*
	(0.0097)	(0.0117)	(0.0432)	(0.0446)	(0.0212)	(0.0379)
ΔP_{m-1}	0.3134*	0.5219***	-0.3505**	-0.2882**	-0.1043	-0.2137
	(0.1661)	(0.1451)	(0.1537)	(0.1357)	(0.2956)	(0.3299)
$\Delta UAH/USD_{m-1}$	0.0039*	0.0020	-0.0217	-0.0221*	0.0123	0.0116
	(0.0021)	(0.0039)	(0.0140)	(0.0115)	(0.0113)	(0.0133)
Observations	35	35	35	35	34	34
R-squared	0.1389	0.5962	0.2143	0.1387	0.0521	0.1216

Notes: This table reports results for the Philips curve at country level. Dependent variable is inflation that is 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 index obtained from estimating model (1) (Columns (5)-(6)). Adjusted inflation measures are nominal inflation measures subtracted by inflation expectations of experts obtained from the NBU Surveys. *U* is the monthly unemployment rate at country level. ΔP_{m-1} is lagged inflation. $\Delta UAH/USD_{m-1}$ is the change in the UAH/USD exchange rate. In all regressions, month of year fixed effects are included but not reported. *, **, and *** denote significance at 10%, 5%, and 1% significance levels, respectively.

Table 5. The Phillips curve – categorical levels

	(1)	(2)	(3)	(4)
	Category		Category - Region	
	Nominal	Adjusted	Nominal	Adjusted
U	0.0396	-0.0769***	0.0607	-0.0757**
	(0.0269)	(0.0277)	(0.0369)	(0.0361)
ΔP_{m-1}	-0.3121***	-0.3196***	-0.4216***	-0.4222***
	(0.0858)	(0.0867)	(0.0199)	(0.0197)
$\Delta UAH/USD_{m-1}$	0.0033	-0.0038	0.0035	-0.0034
	(0.0071)	(0.0066)	(0.0083)	(0.0078)
Obs.	746	746	11,861	11,861
R-squared	0.1317	0.1443	0.1845	0.1857

Notes: This table reports results for the Philips curve at categorical and categorical - regional levels. Dependent variable is (i) categorical level wage index (Columns 1 and 2) and (ii) category - region level wage index (Columns 3 and 4). Adjusted inflation measures are nominal inflation measures subtracted by inflation expectations of experts obtained from the NBU Surveys. *U* is the monthly unemployment rate at country level. ΔP_{m-1} is lagged inflation. $\Delta UAH/USD_{m-1}$ is the change in the UAH/USD exchange rate. 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. *, **, 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	0.0304	-0.0999***	0.0394	-0.1056***
	(0.0185)	(0.0188)	(0.0256)	(0.0256)
ΔP_{m-1}	-0.3185***	-0.3183***	-0.4096***	-0.4095***
	(0.0133)	(0.0131)	(0.0164)	(0.0162)
$\Delta UAH/USD_{m-1}$	0.0026	-0.0037	0.0038	-0.0019
	(0.0048)	(0.0050)	(0.0052)	(0.0057)
Obs.	14,143	14,143	6,986	6,986
R-squared	0.1085	0.1112	0.1836	0.1889

Notes: This table reports results for the Philips curve at occupational - regional level. Dependent variable in Columns (1)-(2) is estimated using the hedonic wage model (model (1)) while dependent variable in Columns (3)-(4) is estimated using the cell median method. Adjusted inflation measures are nominal inflation measures subtracted by inflation expectations of experts obtained from the NBU Surveys. *U* is the monthly unemployment rate at country level. ΔP_{m-1} is lagged inflation. $\Delta UAH/USD_{m-1}$ is the change in the UAH/USD exchange rate. In all regressions, month of year, occupation, and region fixed effects are included but not reported. *, **, 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					
U	-0.9326***	-3.0481***	-2.8131***	-0.2149**	-0.8255**	-0.7685**
	(0.1774)	(0.7593)	(0.6774)	(0.1011)	(0.3439)	(0.3366)
words	0.4467***	0.4349***	0.4373***	0.4109***	0.4191***	0.4176***
	(0.0890)	(0.0881)	(0.0890)	(0.1061)	(0.1083)	(0.1073)
$words^2$	-0.0329***	-0.0312***	-0.0319***	-0.0301**	-0.0323**	-0.0323**
	(0.0092)	(0.0091)	(0.0093)	(0.0115)	(0.0121)	(0.0120)
sentences	-0.1185***	-0.1173***	-0.1179***	-0.1079***	-0.1097***	-0.1100***
	(0.0247)	(0.0245)	(0.0243)	(0.0253)	(0.0254)	(0.0251)
supply			-0.0894***			-0.0807***
			(0.0188)			(0.0195)
Obs.	717,357	717,357	717,357	808,665	808,665	808,665
R-squared	0.3290			0.3505		
F-stat		10.9219	11.2029		6.1582	6.1343
	Panel B. Real wage					
U	-0.8404***	-2.6394***	-2.4075***	-0.1933*	-0.7071**	-0.6495**
	(0.1705)	(0.6880)	(0.6108)	(0.0979)	(0.3165)	(0.3093)
words	0.4476***	0.4376***	0.4400***	0.4107***	0.4176***	0.4161***
	(0.0892)	(0.0883)	(0.0892)	(0.1063)	(0.1083)	(0.1073)
$words^2$	-0.0332***	-0.0317***	-0.0324***	-0.0301**	-0.0320**	-0.0319**
	(0.0092)	(0.0091)	(0.0094)	(0.0115)	(0.0120)	(0.0120)
sentences	-0.1187***	-0.1176***	-0.1182***	-0.1080***	-0.1095***	-0.1099***
	(0.0246)	(0.0245)	(0.0243)	(0.0253)	(0.0254)	(0.0252)
supply			-0.0882***			-0.0815***
			(0.0188)			(0.0198)
Obs.	717,357	717,357	717,357	808,665	808,665	808,665
R-squared	0.2808			0.2825		
F-stat		10.9219	11.2029		6.1582	6.1343
Estimator	OLS	2SLS	2SLS	OLS	2SLS	2SLS

Notes: This table presents results for the wage curve for full sample. Dependent variable is the natural log of offered wage. *U* is (i) the natural log of monthly unemployment rate at country level (Columns (1)-(3)) or (ii) the natural log of the number of unemployed people in a region (Columns (4)-(6)). Panel A reports results for nominal wage while Panel B reports results for real wage. Columns (1) and (4) are estimated using fixed effect estimator. Columns (2)-(3) and (5)-(6) are estimated using instrumental variable estimator. The natural log of number of vacancies to work abroad (*abroad jobs*) is used as the instrument. *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. In all regressions, month of year, year, day of week, category, and region fixed effects are included but not reported. *, **, 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)
	$U = U^{rate}$		$U = U^{unemployed}$	
	Nominal wage	Real wage	Nominal wage	Real wage
	Panel A. 2SLS estimator			
lnW_{t-1}	0.4938***	0.4989***	0.5195***	0.5226***
	(0.0411)	(0.0403)	(0.0421)	(0.0415)
U	-1.4666***	-1.2612***	-0.5311*	-0.4470*
	(0.3923)	(0.3626)	(0.2647)	(0.2367)
words	0.9091***	0.9207***	0.9201***	0.9154***
	(0.2849)	(0.2855)	(0.2816)	(0.2823)
$words^2$	-0.0999***	-0.1015***	-0.1032***	-0.1023***
	(0.0340)	(0.0341)	(0.0333)	(0.0333)
sentences	-0.1371**	-0.1382**	-0.1508**	-0.1486**
	(0.0577)	(0.0567)	(0.0564)	(0.0558)
Obs.	8,770	8,770	10,094	10,094
R-squared	0.2788	0.2819	0.2554	0.2696
F-stat	10.8029	10.8211	5.4261	5.431
	Panel B. GMM estimator			
lnW_{t-1}	0.6831***	0.6819***	0.6753***	0.6431***
	(0.0564)	(0.0518)	(0.0690)	(0.0646)
U	-0.3139***	-0.2501***	-0.1387***	-0.1184***
	(0.0838)	(0.0859)	(0.0406)	(0.0402)
words	0.4720	0.5863	-0.2073	-0.1936
	(0.4011)	(0.3980)	(0.2049)	(0.2356)
$words^2$	-0.0509	-0.0679	0.0374	0.0350
	(0.0571)	(0.0570)	(0.0294)	(0.0338)
sentences	-0.1674*	-0.1678*	-0.0230	-0.0005
	(0.0980)	(0.0949)	(0.0614)	(0.0561)
Obs.	7,852	7,852	9,175	9,175
AR(3) test	0.3431	0.3593	0.4125	0.4332
Hansen test	0.3758	0.1478	0.9804	0.9676

Notes: This table presents results for the wage curve with the autoregressive term of the dependent variable. *U* is (i) the natural log of monthly unemployment rate at country level (Columns (1)-(2)) or (ii) the natural log of the number of unemployed people in a region (Columns (3)-(4)). The 2SLS estimator is employed in Panel A while in Panel B the GMM estimator is used. All regressions are estimated using the cell mean method in which each cell is a pair of occupation – region - month. Dependent variable is the natural log of the cell's average wage. *words* is the natural log of one plus the cell's average number of words in the job description. *sentences* is the natural log of one plus the number of the cell's average sentences in the job description. In Columns (1)-(2) of Panel B, lags 3-5 of wage and lags 3-6 of unemployment are used as instruments. In Columns (3)-(4) of Panel B, lags 3-5 of wage and unemployment variables are used as instruments. In all regressions, U is treated as an endogenous variable with the natural log of number of vacancies to work abroad (*abroad jobs*) used as the external instrument. Month of year, year, occupation, and region fixed effects are included but not reported. *, **, and *** denote significance at 10%, 5%, and 1% significance levels, respectively.

Table 9. The wage curve – by high-/low-skill occupations

	(1)	(2)	(3)	(4)
	Nominal wage		Real wage	
	Low skill	High skill	Low skill	High skill
U	-2.2098***	-0.8010**	-1.8049***	-0.3980
	(0.5705)	(0.3069)	(0.5165)	(0.3308)
words	0.4211***	0.2354***	0.4238***	0.2375***
	(0.0812)	(0.0631)	(0.0814)	(0.0635)
$words^2$	-0.0338***	-0.0109	-0.0343***	-0.0113
	(0.0085)	(0.0072)	(0.0086)	(0.0073)
sentences	-0.1076***	-0.0842***	-0.1079***	-0.0843***
	(0.0211)	(0.0101)	(0.0210)	(0.0101)
Obs.	519,203	65,155	519,203	65,155
F-stat	11.2501	11.3013	11.2501	11.3013

Notes: This table presents results for the wage curve for sub-samples of low-/high-skill occupations. The list of each occupation types is shown in Appendix Table 5. Dependent variable is the natural log of offered wage. Columns (1)-(2) report results for nominal wage while Columns (3)-(4) report results for real wage. In all columns, instrumental variable estimator is used with the natural log of number of vacancies to work abroad (*abroad jobs*) as the instrument. *U* is the natural log of monthly unemployment rate at country level. *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. *, **, and *** denote significance at 10%, 5%, and 1% significance levels, respectively.

Table 10. The wage curve – by region groups

	(1)	(2)	(3)	(4)
	Kyiv	West	Central (excl. Kyiv)	South East
	Panel A. Nominal wage			
U	-0.9019***	-3.9978**	-3.8490***	-1.8203***
	(0.2065)	(1.9017)	(1.1603)	(0.3498)
words	0.2374***	0.4255***	0.7291***	0.4454***
	(0.0543)	(0.0909)	(0.1215)	(0.0992)
words^2	-0.0099*	-0.0336***	-0.0631***	-0.0326***
	(0.0058)	(0.0102)	(0.0131)	(0.0106)
sentences	-0.0902***	-0.1054***	-0.1809***	-0.1208***
	(0.0193)	(0.0225)	(0.0620)	(0.0172)
Obs.	231,269	73,351	83,770	313,770
F-stat	29.4912	3.3713	8.3517	15.1294
	Panel B. Real wage			
U	-0.7016***	-3.6697*	-3.7453***	-1.7209***
	(0.1856)	(1.8106)	(1.1624)	(0.3455)
words	0.2371***	0.4269***	0.7305***	0.4455***
	(0.0544)	(0.0908)	(0.1213)	(0.0992)
words^2	-0.0099*	-0.0338***	-0.0633***	-0.0326***
	(0.0058)	(0.0101)	(0.0130)	(0.0106)
sentences	-0.0902***	-0.1054***	-0.1809***	-0.1209***
	(0.0193)	(0.0225)	(0.0619)	(0.0172)
Obs.	231,269	73,351	83,770	313,770
F-stat	29.4912	3.3713	8.3517	15.1294

Notes: This table presents results for the wage curve for sub-samples of Ukrainian region groups i.e. Kyiv (Column (1)), Western regions (Column (2)), Central regions excluding Kyiv (Column (3)), and South Eastern regions (Column (4)). 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 all columns, instrumental variable estimator is used with the natural log of number of vacancies to work abroad (*abroad jobs*) as the instrument. *U* is the natural log of monthly unemployment rate at country level. *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. *, **, and *** denote significance at 10%, 5%, and 1% significance levels, respectively.

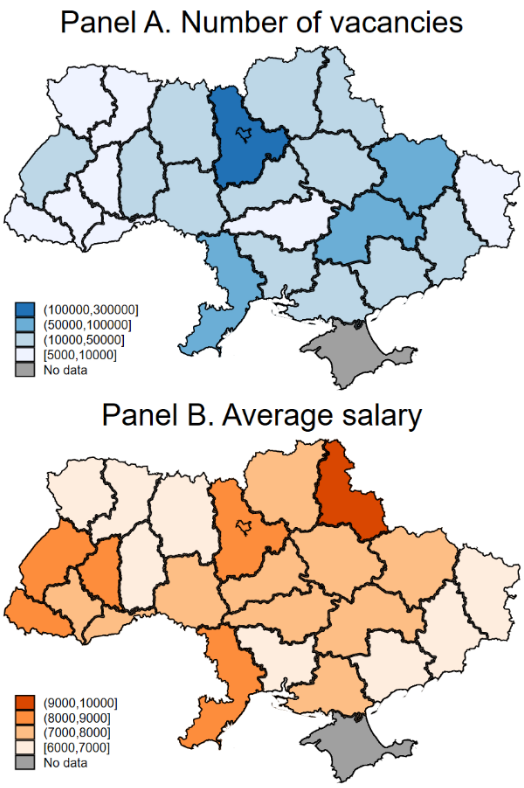
Table 11. The wage curve - effects of visa free regime

	(1)	(2)
	Nominal	Real
U	-9.5356**	-8.0293**
	(3.8513)	(3.7153)
U after visa regime		
07/2017 – 12/2017	2.5595*	1.9444
	(1.4544)	(1.3517)
01/2018 – 06/2018	-3.9385	-3.2437
	(2.7385)	(2.6281)
07/2018 – 12/2018	0.0957	0.1957
	(2.5851)	(2.3105)
words	0.4146***	0.4197***
	(0.0827)	(0.0833)
$words^2$	-0.0271***	-0.0280***
	(0.0082)	(0.0084)
sentences	-0.1161***	-0.1164***
	(0.0247)	(0.0246)
Obs.	708,619	708,619
F-stat	1.6552	1.6552

Notes: This table presents results for the effect of the visa free regime on the elasticity of the wage curve. Dependent variable is the natural log of offered wage. Column (1) reports results for nominal wage while Column (2) reports results for real wage. In all columns, instrumental variable estimator is used with the natural log of number of vacancies to work abroad (*abroad jobs*) as the instrument. *U* is the natural log of monthly unemployment rate at country level. *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. *, **, and *** denote significance at 10%, 5%, and 1% significance levels, respectively.

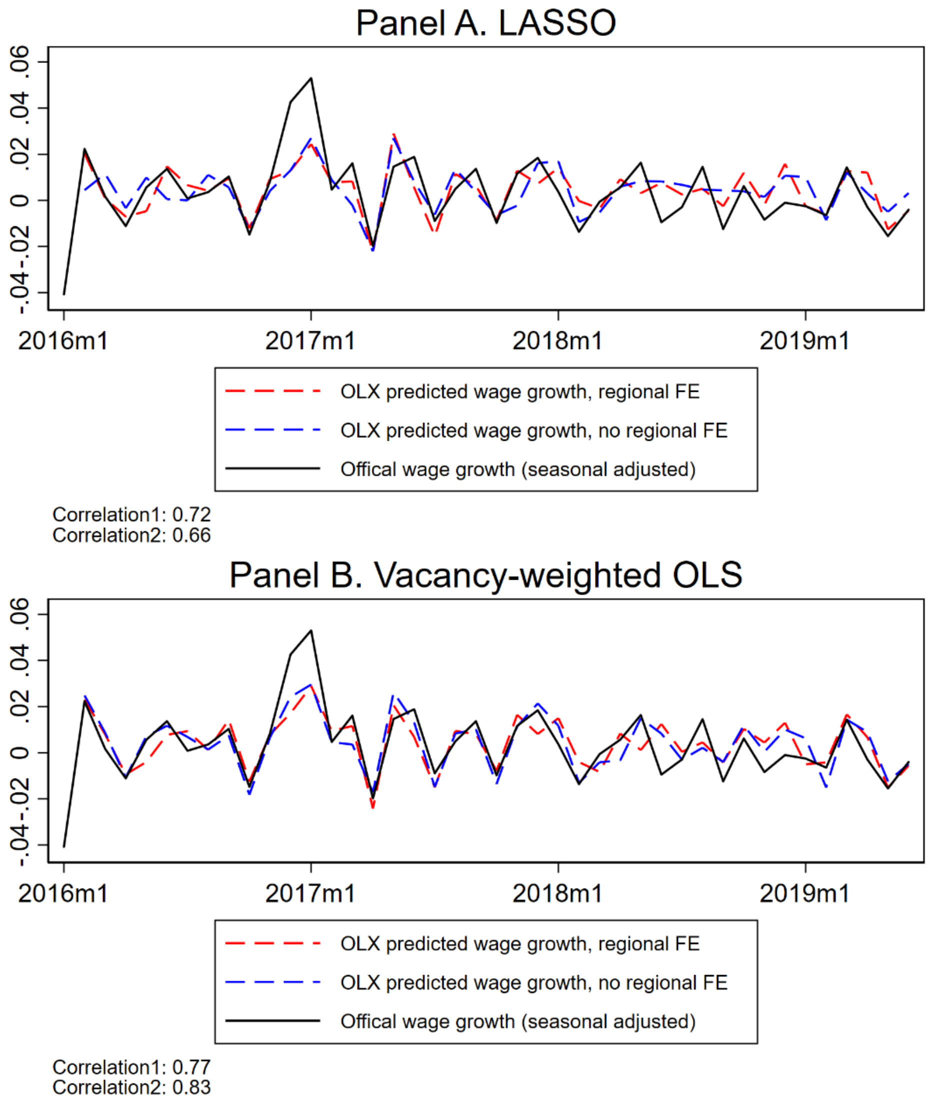
Figures

Figure 1. Number of vacancies and average salaries by region



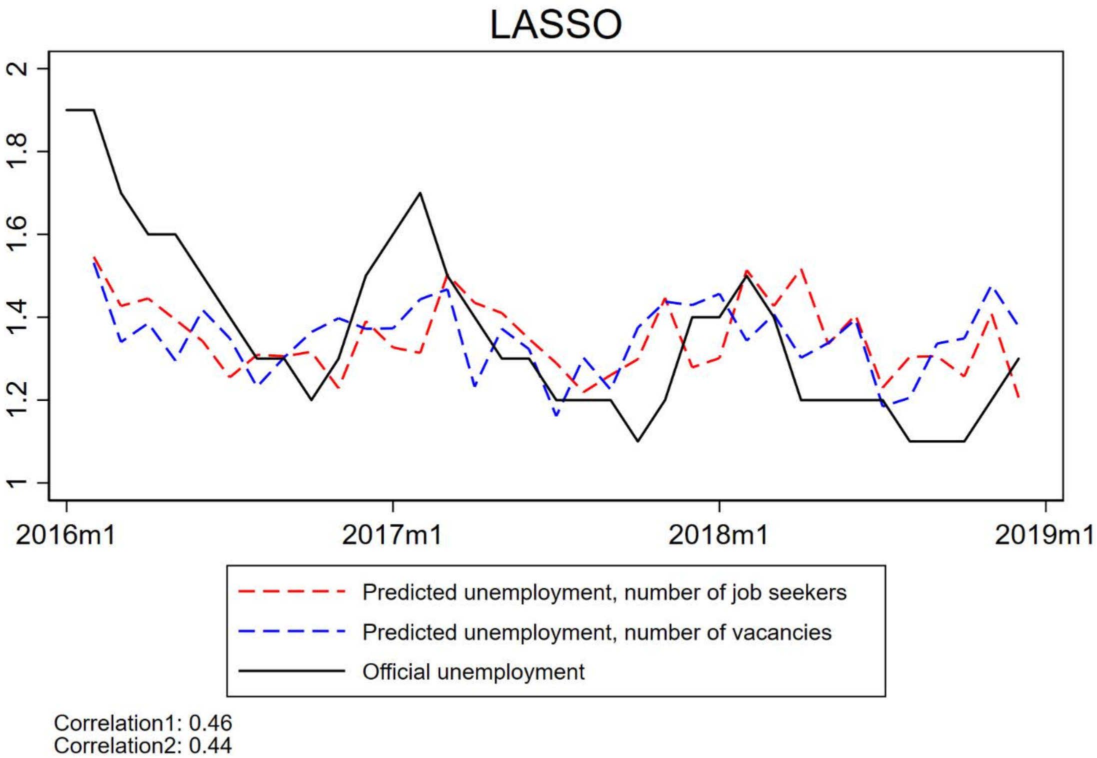
Notes: This figure shows the number of vacancies the average monthly salaries by regions of Ukraine (Panels A and B, respectively). The darker colour means the higher number of vacancies/higher average salary. The grey area represents Crimea which is the occupied region and is not included in the analysis.

Figure 2. Official and Online OLX Wage Indexes



Notes: This figure shows the correlation between predicted wage growth using OLX-based categorical wage index and the official wage growth. 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.

Figure 3. Unemployment



Notes: This figure shows the correlation between predicted unemployment using OLX data and the official unemployment rate. The solid black line, the dashed red line, and the dashed blue line represent the official unemployment, the predicted unemployment using the natural log of number of job seekers, and the predicted unemployment using the natural log of number of vacancies, respectively. Correlation 1 is the correlation score between the first and second unemployment rates while Correlation 2 is the correlation score between the first and third unemployment rates. The predicted unemployment rates are obtained from the LASSO approach.

Appendix

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

	(1)	(2)	(3)	(4)	(5)	(6)
	Vacancies			Salary		
	Total	Mean	P25	P50	P75	SD
Kyiv	260,727	8,935	5,000	7,500	11,000	5,889
Dnipropetrovsk	87,894	7,513	3,600	5,500	9,500	5,791
Odesa	78,380	8,175	4,500	7,000	10,000	5,291
Kharkiv	66,013	7,297	4,000	6,000	9,000	4,982
Zaporizhzhya	39,533	6,419	3,200	5,000	7,700	5,069
Donetsk	31,548	6,813	3,000	5,000	8,000	6,085
Poltava	23,759	7,271	3,250	5,000	9,000	5,866
Lviv	23,514	8,008	4,000	6,100	10,000	6,102
Mykolayiv	21,823	6,927	3,250	5,000	8,000	5,674
Kherson	18,746	7,213	3,500	5,000	8,500	5,917
Vinnytsya	16,945	7,324	3,500	5,000	9,000	5,971
Cherkasy	16,883	7,015	3,000	4,950	8,500	5,934
Chernihiv	15,270	7,774	3,250	5,000	10,000	6,596
Zhytomyr	14,660	6,989	3,497	5,000	8,001	5,553
Sumy	13,777	9,612	3,500	6,500	15,000	7,616
Khmelnytskiy	13,109	6,751	3,450	5,000	8,000	5,340
Rivne	9,879	6,664	3,000	5,000	8,000	5,709
Luhansk	9,832	6,850	2,950	4,500	8,500	6,559
Volyn	9,828	6,813	3,000	5,000	8,000	5,816
Kropyvnytskyi	9,433	7,963	3,250	5,000	10,500	6,664
Ivano-Frankivsk	9,094	7,426	3,500	5,450	9,000	6,256
Zakarpattya	6,765	8,481	4,000	6,100	10,000	7,011
Chernivtsi	6,002	7,646	4,000	6,000	9,500	5,592
Ternopil	5,251	8,024	3,750	6,000	10,000	6,596

Notes: This table reports statistics on salary (in UAH) and number of vacancies by regions. Column (1) shows the total number of vacancies. Columns (2)-(5) show the average, 25^{th} percentile, median, and 75^{th} percentile salaries, respectively. Column (6) shows the standard deviation of salary.

Appendix Table 2. The Phillips curve – country level (Different inflation expectation adjustments)

	(1)	(2)	(3)
	Household	Business	Bank
U	-0.0591*	-0.1383***	-0.0946**
	(0.0310)	(0.0428)	(0.0453)
ΔP_{m-1}	-0.0095	0.0880	-0.0142
	(0.2115)	(0.1527)	(0.2384)
$\Delta UAH/USD_{m-1}$	0.0070	0.0056	0.0096
	(0.0115)	(0.0142)	(0.0133)
Obs.	34	34	34
R-squared	0.0549	0.2693	0.1400

Notes: This table reports results for the Philips curve at country level. Dependent variable is the country-level OLX wage index obtained from estimating model (1) (Columns (5)-(6)). Adjusted inflation measures are nominal inflation measures subtracted by inflation expectations of household, business, and bank obtained from the NBU Surveys (Columns (1)-(3), respectively). *U* is the official unemployment rate. ΔP_{m-1} is lagged inflation. $\Delta UAH/USD_{m-1}$ is the change in the UAH/USD exchange rate. In all regressions, month of year fixed effects are included but not reported. *, **, and *** denote significance at 10%, 5%, and 1% significance levels, respectively.

Appendix Table 3. First stage results

	(1)	(2)	(3)	(4)
	$U = U^{rate}$		$U = U^{unemployed}$	
abroad jobs	-0.0160***	-0.0162***	-0.0583**	-0.0582**
	(0.0048)	(0.0048)	(0.0235)	(0.0235)
words	-0.0059***	-0.0059***	0.0118**	0.0118**
	(0.0018)	(0.0018)	(0.0050)	(0.0050)
$words^2$	0.0011***	0.0010***	-0.0027***	-0.0027***
	(0.0003)	(0.0003)	(0.0009)	(0.0009)
sentences	0.0008**	0.0008**	-0.0019*	-0.0019*
	(0.0003)	(0.0003)	(0.0010)	(0.0010)
supply		-0.0045*		0.0023
		(0.0024)		(0.0042)
Obs.	717,357	717,357	808,665	808,665

Notes: This table presents the results for the first stage. Dependent variable is the natural log of monthly unemployment rate at country level (Columns (1)-(2)) or the natural log of number of unemployed people in a region (Columns (3)-(4)). *abroad jobs* is the natural log of number of vacancies to work abroad. *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. *, **, and *** denote significance at 10%, 5%, and 1% significance levels, respectively.

Appendix Table 4. Wage curve – compare high/low-skill occupations

	(1)	(2)
	Nominal wage	Real wage
U	-2.6067***	-2.1802***
	(0.6828)	(0.6128)
U×Low skill	-0.4234***	-0.4231***
	(0.0806)	(0.0807)
words	0.4403***	0.4431***
	(0.0867)	(0.0869)
words^2	-0.0328***	-0.0333***
	(0.0090)	(0.0090)
sentences	-0.1116***	-0.1120***
	(0.0236)	(0.0236)
Obs.	717,357	717,357
F-stat	3.5411	3.5411

Notes: This table presents results for impact of low-/high-skill occupations on the elasticity of the wage curve. The list of each occupation types is shown in Appendix Table 6. Dependent variable is the natural log of offered wage. Column (1) reports results for nominal wage while Column (2) reports results for real wage. In all columns, instrumental variable estimator is used with the natural log of number of vacancies to work abroad (*abroad jobs*) as the instrument. *U* is the natural log of monthly unemployment rate at country level. *Low skill* is a dummy variable which equals to 1 if a job if a low-skill occupation and 0 otherwise. *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. *, **, and *** denote significance at 10%, 5%, and 1% significance levels, respectively.

Appendix Table 5. Wage curve – additional instrument

	(1)	(2)	(3)	(4)
	$U = U^{rate}$		$U = U^{unemployed}$	
	Panel A. Nominal wage			
U	-2.9695***	-2.7699***	-0.7865**	-0.7405**
	(0.7309)	(0.6641)	(0.3343)	(0.3278)
words	0.4354***	0.4376***	0.4186***	0.4172***
	(0.0881)	(0.0890)	(0.1082)	(0.1073)
$words^2$	-0.0313***	-0.0320***	-0.0322**	-0.0322**
	(0.0091)	(0.0093)	(0.0120)	(0.0120)
sentences	-0.1173***	-0.1179***	-0.1096***	-0.1100***
	(0.0245)	(0.0243)	(0.0254)	(0.0252)
supply		-0.0892***		-0.0808***
		(0.0188)		(0.0196)
Obs.	717,357	717,357	808,665	808,665
overid	0.2733	0.4099	0.3377	0.4781
underid	0.0142	0.0138	0.3314	0.3298
F-stat	6.9424	7.0728	3.5877	3.5825
	Panel B. Real wage			
U	-2.5422***	-2.3474***	-0.6632**	-0.6168*
	(0.6644)	(0.6018)	(0.3088)	(0.3027)
words	0.4381***	0.4403***	0.4170***	0.4156***
	(0.0883)	(0.0892)	(0.1083)	(0.1073)
$words^2$	-0.0318***	-0.0325***	-0.0318**	-0.0318**
	(0.0091)	(0.0094)	(0.0120)	(0.0120)
sentences	-0.1177***	-0.1182***	-0.1094***	-0.1098***
	(0.0245)	(0.0243)	(0.0255)	(0.0252)
supply		-0.0880***		-0.0817***
		(0.0188)		(0.0198)
Obs.	717,357	717,357	808,665	808,665
overid	0.1913	0.2875	0.2746	0.3915
underid	0.0142	0.0138	0.3314	0.3298
F-stat	6.9424	7.0728	3.5877	3.5825

This table presents results for the wage curve. 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 all columns, instrumental variable estimator is used with (i) the natural log of number of vacancies to work abroad (*abroad jobs*) and (ii) the natural log of number of job seekers looking for abroad jobs (abroad seekers) as the instruments. *U* is the natural log of monthly unemployment rate at country level. *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. In all regressions, month of year, year, day of week, category, and region fixed effects are included but not reported. *, **, and *** denote significance at 10%, 5%, and 1% significance levels, respectively.

Appendix Table 6. List of high-skill and low-skill occupations

High-skill occupations	Low-skill occupations
Accountant, Administrator, Analyst, Auditor, Dentist, Developer, Director, Doctor, 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 belong to high-skill and low-skill occupations.