The Labor Market Impact of the War in Donbass

by

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Abstract

In the Spring of 2014, war between Ukrainian government forces and proxies of the Russian government -- assisted by Russian soldiers -- broke out in the eastern Ukrainian Oblasts (equivalent of a US state) of Donetsk and Luhansk. The resulting war, which continues today, created over 1.3 million internally displaced persons (IDPs), including hundreds of thousands who moved into Oblasts which did not directly experience conflict. Since then, there have been few studies looking at the Ukrainian labor market and none looking at the wars economic impact on it. This paper uses panel data from 2010 to 2018 to measure the economic impact of the labor supply shock caused by the 2014 War in Donbass in oblast level labor markets that did not directly experience conflict. We measure that impact with changes in average wages and changes in unemployment in the studied Oblast labor markets. Using econometric analysis, we thereby study the ability of Ukrainian labor markets to adjust to shocks in their current post-Soviet environment. We find a negative and statistically significant impact on wages and a statistically insignificant impact on unemployment. The results of this paper can help provide an accurate picture of the current Ukrainian labor market by highlighting rigidities in the labor market.

Introduction

In the Spring of 2014, Russia invaded Ukraine, seizing Crimea and launching a war between Ukrainian government forces and proxies of the Russian government -- assisted by Russian soldiers – that broke out in the eastern Ukrainian Oblasts (equivalent of a state in the US) of Donetsk and Luhansk. The resulting war, which continues today, created over 1.3 million internally displaced persons (IDPs), including hundreds of thousands fleeing into Oblasts which did not directly experience conflict. Since then, there have been few studies looking at the Ukrainian labor market and none looking at the war's economic impact on it.

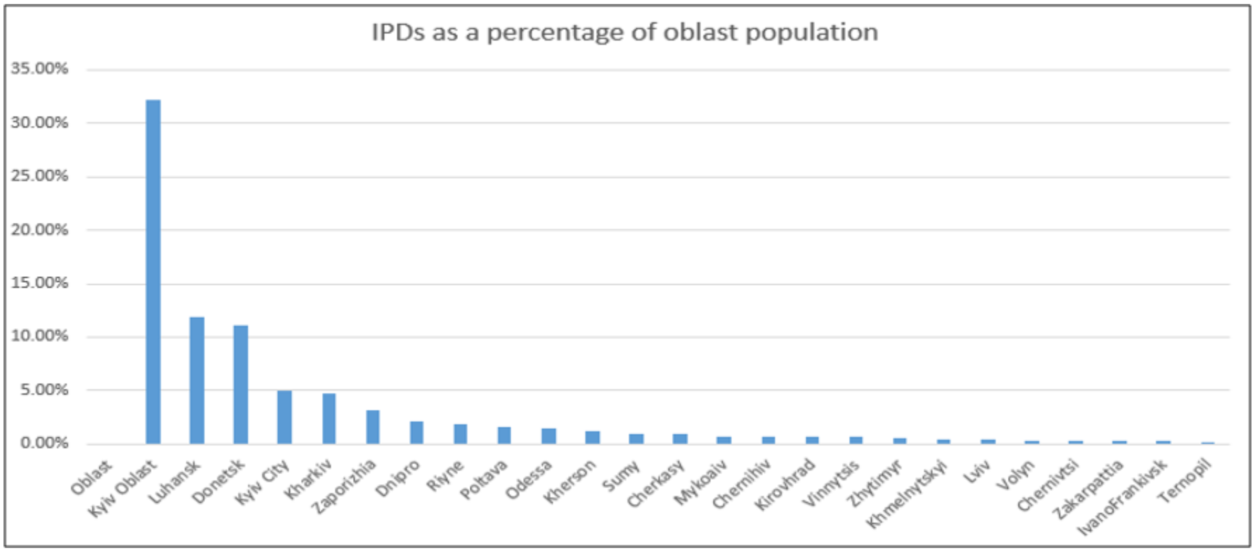
This paper uses panel data from 2010 to 2018 to begin to study that impact. We measure the economic impact of the labor supply shock caused by the 2014 War in Donbass on the labor markets in oblasts that did not directly experience conflict. Assuming the IDPs join the workforce in their new locations, basic economic theory predicts the primary initial economic impact will be an increase in labor supply i.e. a rightward shift in the supply curve, decreasing the equilibrium market wage. Empirical economic research suggests that the effect on wages is more ambiguous, with certain papers suggesting an effect around statistical zero (Boustan, 2010, and Frank, 2009) while others do not (e.g. Calderon, 2009). This departure could be explained multiple ways. The casual relationship could be more complex than basic economic theory suggests meaning other variables could be an important factor. The result could also reflect local economic institutions. A deeper discussion of the literature will be later in the paper.

Using econometric analysis, we analyze the reaction of Ukrainian labor markets to shocks in their current post-Soviet environment. That environment is now changing as the new Ukrainian government is currently attempting to overhaul the Ukrainian labor code for the first time since the 1970s (Kokriatski, 2020). There are many unanswered questions about the Ukrainian labor market. How did local markets react to the 2014 war? Did they react in a way that is consistent with known market analysis? How might labor market outcomes be improved? The results of this paper can help improve our understanding of the current Ukrainian labor market by highlighting possible rigidities in the labor market.

Background

On April 7, 2014—following months of protest and Russia's seizure of the Crimean Peninsula -- government buildings were stormed and taken over in regions with large populations of ethnic Russians. While peace was restored in most oblasts, Luhansk and Donetsk persisted leading to the national government declaring Anti-Terrorist Operations (ATO) on April 15 (Bartkowski, 2015). Through the following weeks the crisis devolved into a full-scale war -- which continues today -- between Ukrainian forces and Russian proxies and Russian forces leading to the death of over 3,000 civilians and internal displacement of 1,373,675 as of March 2019 (National Monitoring, 2019). Of those almost 1.4 million Internally Displaced Persons (IDP), 417,292 moved out of the Donetsk and Luhansk Oblasts. The most impacted Oblast was Kyiv with an incoming IDP population being equal to 32% of the 2015 population. Luhansk and Donetsk had an IDP population equal to 11% of their 2015 population. The City of Kiev, Kharkiv, Zaporizhia, Dnipro, Riyne, Poltava, Odessa, and Kherson all had IDP populations between 1% and 5.1% of their 2015 population. All other oblasts had IDP populations less than 1% of their 2015 population. Luhansk and Donetsk were not included in the analysis.

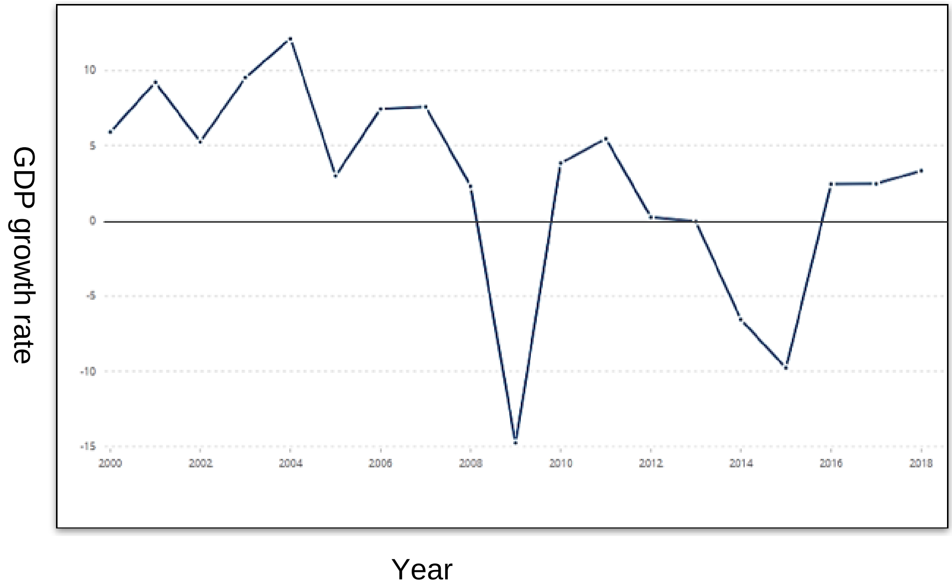
Figure 1: Cumulative IDPs as a percentage of each oblast's population



This paper looks at the economic impact of those 417,292 IDPs on the labor markets of the 22 non-war-thorn Ukrainian Oblasts. We use quarterly net migration data from 2010 to 2018 collected by the State Statistics Service to estimate the economic impact on wages and unemployment.

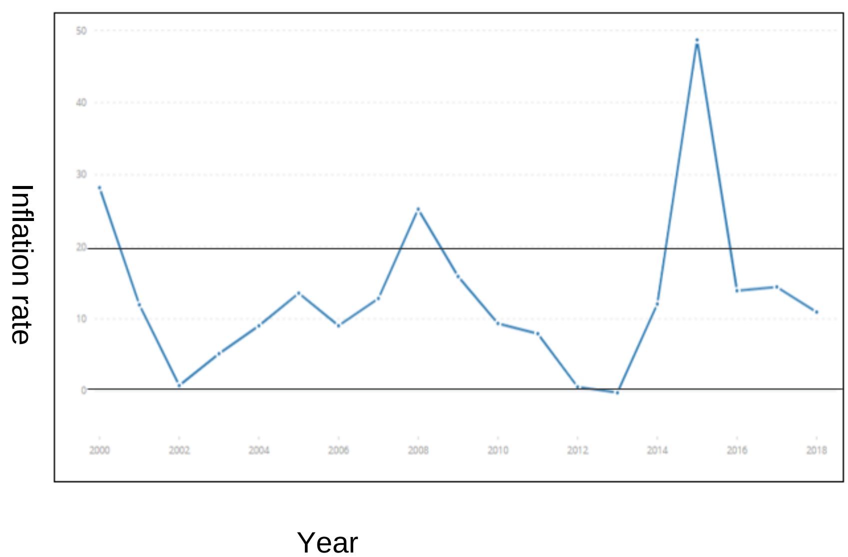
Ukrainian labor laws have been governed by the *Labor Code of Ukraine* which was adopted in December 1971 by the Ukrainian SSR (Про Затвердження, 1971). It was developed for a command economy in which all markets, including labor markets, were suppressed. Ukrainian labor laws have been almost untouched since. There have been multiple attempts at reform with the most recent being in early 2020 by the newly elected President Volodymry Zelensky — who was not born for almost a decade after the labor code was passed -- (Kokriatski, 2020). The code is also long -- 87 pages in 18 chapters — and regional and local governments have little room to make specific reforms or local adjustments. Like other past reform attempts, the latest reform bill was scuttled by pressure from labor unions (Government, 2020).

Figure 2: Annual GDP growth rate 2000 - 2018



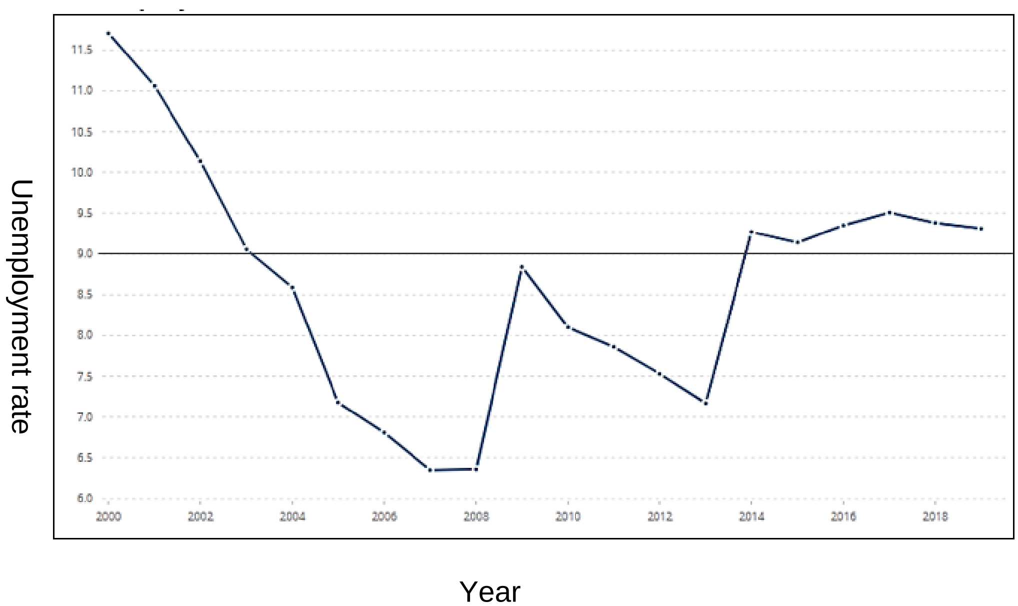
Prior to the breakout of the war, the Ukrainian economy was a mixed bag. From the turn of the 21st century until late 2008, Ukraine saw positive GDP growth in every quarter. Since then, the economy has seen spurts of growth and contraction prior to 2014. Starting in 2014, there was an economic contraction caused by the war and political instability, with recovery in 2016 to steady growth.

Figure 3: Annual inflation rate 2000 – 2018



For most of the 21st century until 2011, Ukraine saw inflation over five percent but was generally able to keep it under ten percent outside the global financial crises. Starting in mid-2011 inflation began to decline until reaching a slightly deflationary status 2012 and staying there until early-2014. It naturally peaked in 2015 with the economic disruption caused by the war, but then returned to 10-15% to 2018.

Figure 4: Annual unemployment rate 2000 – 2018



When it comes to unemployment, Ukraine experienced a steadily declining unemployment rate of 9.8% in quarter one of 2004 to 6.5% in quarter three in 2008. By the first quarter of 2009, unemployment was over 10% and never got below 7% for more than a quarter at a time since 2009. Since the 2014 recession, unemployment has been at a new elevated rate of 9-9.5%.

Literature Review

This paper contributes to two different literatures -- that on the Ukrainian labor market and the literature on the impact of internal migration on local labor markets. When it comes to the Ukrainian labor market literature, much of the relevant literature either is prior to the outbreak of the war or does not address its economic impact. I was only able to identify one Ukrainian labor market study which mentioned the war (Lukianenko, 2017). The large gap in the literature creates a significant problem. Ukraine has one of Europe's largest populations and is its largest country in terms of area. It also has struggled to abandon its Soviet past and liberalize its economy. One of the area’s most in need of reform is labor markets. As of January 2020, the Zelensky government is attempting the first overhaul of the Ukrainian labor code since the 1970s. The proposed reform introduces multiple important changes to the law including at will employment, minimum union sizes, limiting the number of unions per enterprise, and limiting union protections (Kokriatski, 2020). The goals of these reforms are to limit the size of the labor black market, promote dynamism, and increase economic growth.

In this paper we study how IDPs from the Donetsk and Luhansk regions impacted the labor markets they moved to after the war broke out. The influx into non-war-torn oblasts would be relatively small in its magnitude. The results of this paper would help fill in critical details which the current literature has not addressed and perhaps thereby providing the basis for more potent reforms. By providing specific quantitative measurements on Ukrainian labor market relations, policy makers could better target their reforms.

This study also builds on the published literature looking at the impact of internal migration on local labor markets. While the research looking at the impact of immigration is rich, the number of studies looking at impact of internal migration on labor markets is relatively sparse. Internal migration and immigrants could potentially have different impacts because of language differences, skill differences, culture differences, or legal barriers (Jamil, 2012). Most of the internal migration labor impact research focuses on causes not impacts. Research has shown labor supply shocks caused by internal migration in the United States during the Great Depression were adjusted to in the local labor market by reductions in the quantity of employment rather than in lower wages (Boustan, 2010). Boustan (2010) found for the inflow of 37,000 males from Dust Bowl effected regions has a substantial economic impact on 21,7000 Californian males. They found for every 10 arrivals, 1.9 residents left the area, 2.1 residents were forced out of the labor market and 1.9 residents went from full-time employment to part-time employment. Their reduction in wages was statistically insignificant. The study exploited variation between labor markets to control for the macroeconomic contraction. Another study looking at internal migration in post-unification Germany, found no significant wage effect but a one percent increase in the population of east German migrants increased the employment rate by 1.4% the next year (Frank, 2009).

Other research has partially confirmed and partially disputed these findings. A study looking at the impact of conflict induced migration in Colombia found a 1.4% reduction in wages for a 10% increase in the share of migrants (Calderon, 2009). These results were supported by another study that found a 1% increase in conflict induced population in Colombia lowered wages by 1.4% the following year and a 1% conflict induced population increase raised the rate of out-migration of 0.2% (Morales, 2017). Similarly, a study looking at Canadian internal migration found an increase in internal migration had “a rather small" negative effect on the growth of wages while also finding a strong effect on unemployment (Wrage, 1981). The simplest way to summarize these studies is to note their results tend to be either insignificant or small.

Expected Results and Approach

Overall, I expected this paper to find results in line with economic theory. According to standard economic theory, when the supply of labor increases, in a well-defined market, -- as would result from a positive labor supply shock -- there would be an impact on both dependent variables this study looks at, at least in the short run. An increase in the labor force would be expected to decrease wages -- demand curves are downward sloping after all. Conversely, the addition of different workers would have an ambiguous effect on unemployment. It would likely depend on the composition of the internally displaced persons — data we don’t have — and where they moved to. Essentially, I expect a negative coefficient when looking at wages and have no expectation when I’m looking at unemployment. Identifying well-defined labor markets was a key challenge in this paper.

One of the purposes of this study is to examine the strength of Ukrainian labor markets in the post-Soviet environment. If the study found it’s expected results -- a negative coefficient when looking at wages -- that would suggest Ukrainian labor markets are healthy and responded to changes in the economic environment. If the coefficient did not match our expected results, that would suggest our model was misspecified. For example, one shortfall we considered too late too address was the outflow of Ukrainian men out of the labor markets and into the armed forces. Our model does not capture that effect. If both results were different than the expected signs that would suggest Ukrainian labor markets are not healthy but would leave other potential explanations as well. The Ukrainian State Statistics Service could be failing to be capturing accurate economic information in their economic statistics -- either because of a flawed data generation process or because of significant economic activity happening off the books in black-markets. Another explanation would be a faulty methodology. A true and unbiased but significant value could have failed to be discovered because of an insufficiently refined methodology.

This paper looks at the impact IDPs from Donetsk and Luhansk had on labor markets in oblasts not directly affected by military conflict. In order to get data with higher frequency, net migration to each oblast is used as a proxy for IDP movement, because that is the only quarterly available data. Because net migration between regions is relatively constant and there is no other significant event to cause large movements in the population, any large changes in net migration is likely because of the 2014 war. The descriptive statistics for net migration are shown below.

This paper looks at a variety of variables. The independent variable used was labor force for each oblast for every time period observed (x, it). The corresponding dependent variables (y, it) were nominal wages and unemployment. Nominal wages were used because inflation was fairly stable outside of 2014, 2015, and 2016. Each variable had an observation collected for each quarter from quarter one 2010 until quarter one 2018 -- totaling 825 observations. The data was collected from the State

Statistical Service of Ukraine website. To control for confounding factors, control variables were used for oblast fixed effects (Φ), time fixed effects (Ꞇ), a proxy for local institutions (Ᵽ), and gross regional product of the prior quarter (Ǥ). The descriptive statistics for the dependent and independent variables are below.

Figure 5: Descriptive statistics

	Labor Force, thousands of persons	Net Migration, Persons	Unemployment, Thousands of persons	Wage, Hryvnia(₴)
Number of observations	736	736	736	736
Mean	746.873	91.346	62.402	3,611.924
Standard deviation	339.68	800.215	20.589	1,652.379
Minimum	387.6	-1743.0	27.2	1,672.0
25%	523.0	-208.0	48.875	2,460.335
Median	590.35	-38.0	56.6	2,993.0
75%	824.575	97.0	72.3	4,359.6675
Max	1,679.3	8,061.0	145.4	12,393.45

The first series of models we ran employed Ordinary Least Squares (OLS). The results here tended to cluster around statistical zero. Models estimating the impact of net migration on unemployment were systematically weaker than models estimating the impact on wages. These results were believed to be a result of inadequate model specification. To improve our results, and deal with endogeneity problems, we switched to a two stage least squares (2SLS) model using changes in the variables of interest (average wages and Oblast unemployment) as the dependent variable and changes in the labor force as the independent variable, with net migration — proxying for IDPs -- as the instrumental variable.

In the first stage net migration was used as an instrumental variable to generate predicted values for the change in the labor force to eliminate endogeneity. Those predicted replace the original *x* value and are represented by *px*. Net migration was directly correlated with labor force but, being exogenously forced, was assumed not correlated with wages or unemployment. With this experimental design, we will be able to see the impact IDPs had on labor markets on non-impacted regions. Net migration to each oblast is used as a proxy for the number of IDPs — albeit a far from perfect one.

OLS Equation: $\Delta Y_{it} = \beta_1 \Delta x_{it}$ + (Conflcit: Δx_{it}) $+\beta_2 \Phi_i + \beta_3 Ᵽ_i -1 + \varepsilon$

First Stage Equation: $\Delta x_{it} = \beta_0 + \beta_1 IV_{it} + \beta_2 \Phi_i + \beta_3 Ᵽ_i -1 + \varepsilon$

Second Stage Equation: $\Delta Y_{it} = \beta_1 p \Delta x_{it}$ + (Conflcit: Δx_{it}) $+\beta_2 \Phi_i + \beta_3 Ᵽ_i -1 + \varepsilon$

In the regressions, Φ is used control for fixed effects across both oblasts which allowed us to identify the labor markets at the oblast level. Ᵽ represents how an oblast voted in the 2014 Presidential election as measured by the share of each oblast that voted for reformist candidate Petro Poroshenko. The 2014 vote share was used as a control because I believe the more an Oblast was to vote for Poroshenko the stronger the reformist elements would be in the city and oblast governments, and hence the more liberal or reformist their interpretation of the Soviet Labor Code. Why do we care about which oblasts have stronger liberal or reformist elements? That ties back to the 1971 law. It was meant to stifle markets and enforce labor discipline. Reformist regions would be more likely to interpret the law in a way that allows more market function. In these regions, we would expect results closer to standard market outcomes than in regions which varied from the 1971 law.

We also worked with alternative model specifications in our investigation which are not presented here. We worked with time fixed effects, but those controlled for too much of the variation. We looked at percent changes in our dependent and independent variables, but those provided noisier results. We also looked at the impact of different interesting control variables like the percent of the informal workforce, Gross Regional Product, or different economic makeups.

Panel Results

The first result we'll look at is the simple relationship between the predicted labor force — PX -- and wages, without any controls. Only the second stage will be shown but all stages can be seen in the appendix.

Figure 6: Labor force ~ wage 2SLS result

Variable	Coefficient	Std. Error.	P > t
Intercept	1539.8062	343.040	0.000
Predicted labor force	2.8473	0.453	0.000

For our first set of regressions (Figure 6) — the naïve labor force regressed against wages -- the coefficient is a positive 2.8473 meaning for every increase in the predicted labor force by 1,000 there is an increase in wages by 2.85 Hryvnia. The p-value is zero to the third decimal place meaning the result is statistically significant at the one percent confidence level. Similarly, the regression only explains 5.3% of the variation in the observations.

This result presents a significant issue that took up a lot of time solving. As noted, the coefficient here is positive which goes against the expected results. The obvious hypothesis for the impact of an increase in the labor force would have on wages would be a decrease on wages because demand curves slope downward. As the quantity of labor increases, we would expect the wage for that market to decrease. In this case the results suggest more labor increases the wage. That suggested we failed to correctly identify the market demand curve in our first regressions. Later in this paper, we will address how we found the market demand curve.

Figure 7: Labor force ~ unemployment 2SLS result

Variable	Coefficient	Std. Error.	P > t
Intercept	32.7955	4.264	0.000
Predicted labor force	0.0397	0.006	0.000

Next, we have our second regression (Figure 7) —labor force and unemployment. We have the second stage estimation for our predicted labor force represented by PX and the number of unemployed. As you can see the coefficient is a positive 0.0397 meaning for every increase in the predicted labor force by 1,000 there is an increase in the number of unemployed by 40 persons. The p-value is zero to the third decimal place meaning the result is statistically significant at the one percent significance level. Similarly, the regression only explains 6.5% of the variation in the observations.

Next, we have our third regression (Figure 8) —labor force and wages with controls. To properly identity the labor demand curve we made multiple changes to our model specification to improve our results. First, we focused on the relation between changes in labor and changes in wages or unemployment between quarters to more directly capture the labor demand curve. We controlled for regional fixed effects and local variation in institutional quality through the proxy variable. We also had an interaction term between a conflict dummy and the change in labor force force to measure the impact of the conflict. We interacted the war period with net migration to better show the differences in impact of net migration between the war and the pre-war period. Our war period dummy variable went from the pre-war zero to war one at 2014 quarter 2.

Figure 8: Labor force ~ wage 2SLS result

Variable	Coefficient	Std. Error.	P > t
Predicted labor force	-24.1208	9.259	0.009
Conflict:Predicted LF	0.5847	0.069	0.000
Institutional Control	446.7552	152.494	0.004
Regional fixed effects		Yes	

Above we have the second stage estimation for our predicted labor force represented by PX and the change in wages. As you can see the coefficient is a negative 24.1208, meaning for every increase in the predicted labor force by 1,000 there is a decrease in the change in wages by 24.12 Hryvnia. This result is in line with what we would expect in a functioning market economy. The p-value is 0.009 meaning the result is statistically significant at the one percent significance level. The regression also explains 83.4% of the variation in the observations.

Figure 9: Labor force ~ unemployment 2SLS result

Variable	Coefficient	Std. Error.	P > t
Predicted labor force	-0.2246	0.227	0.324
Conflict : Predicted LF	0.0012	0.002	0.486
Institutional Control	4.5695	3.746	0.223
Regional fixed effects		Yes	

Finally, we have our fourth regression (Figure 9) —labor force and unemployment with controls. This table presents the second stage estimation for our predicted labor force, represented by PX, and change in the number of unemployed. As you can see, the coefficient is a negative 0.2246 meaning for every increase in the predicted labor force by 1,000 there is decrease in the change of the number of unemployed by 225 persons. The p-value is 0.324 meaning the result is statistically insignificant at the ten percent significance level. The regression explains 88.4% of the variation in the observations. While the sign of our coefficient did change, our hypothesis was an ambiguous effect on unemployment.

These results also supported the usage of a 2SLS model with net migration as the instrument. The final stage results showed much lower F-statistics compared to the first stage and low standard errors.

Overall this study was able to answer most of the questions it asked. How did wages respond to the war caused shock? The wages from quarter to quarter declined with the increase in the predicted change in labor force in a small but statistically significant amount. How did unemployment respond? The change in unemployment was ambiguous as our result was statistically insignificant. When we hypothesized our expected results earlier, we expected an ambiguous effect because we believed the result would depend on the composition of the internally displaced persons and where they moved to. If we were correct in that hypothesis, our insignificant result is from an insufficiently detailed specification. The biggest shortcoming of this study is failing to sufficiently specify a developed labor force unemployment model so the results would be statistically significant.

While this paper is limited, it provides a foundation several clear improvements that could be made which would guide how this research is improved if continued. First, better data on the characteristics on the IDPs leaving Donetsk and Luhansk and where they went. Someone who spent their whole lives working in coal mines would have greater trouble reentering the labor market in a region which didn't have coal mines than someone who worked in a more general field.

Similarly, while we considered the quality of local governments, we did not consider welfare support by the national government for IDPs. Depending on the level of support, IDPs could be pushed into the labor force quicker or slower than otherwise. For example, if a family which was displaced received generous support from the government then they would be able to be more selective of employment options because they could stay out longer.

Lastly, one issue we didn't consider until late in the process was Ukrainian men leaving their local labor force to join the military and fight in the east. While the inflow of refugees was a positive shock the mobilization was a negative shock. The effect of these two shocks would be ambiguous without knowing the magnitude of each. An improvement to the data could be adjusting net migration figures with mobilization numbers.

Conclusion

The War in Donbass has had an immense human cost and impact well beyond the Donetsk and Luhansk Oblasts. This study attempts to estimate some of the economic impact IDPs from the conflict zone had on the labor markets of non-war-torn Oblasts. We do not have quarterly data on IDPs, and so had to attempt to instrument them. The first stage of our two stage least squares attempts to do this with the net migration instrument.

Our preliminary investigation suggested an increase in the labor force has a slight positive to insignificant impact on wages depending on the specification of the model. This result contradicted what we would expect from economic theory. We were able to fine tune our model to better identify the labor market demand curve. In doing so, we found an increase in labor force leads to a significantly significant decrease in wages. We also found a negative, but statistically insignificant, impact on unemployment. Both these results fit our hypothesis of a negative impact on wages and an ambiguous impact on unemployment.

This investigation also consistently found that models estimating the impact of labor force on unemployment were stronger than the models investigating the impact of labor force on wages. This shouldn't be too surprising since there is more of a direct relationship. This investigation found simpler models had stronger and more statistically significant results, but with the theoretically wrong sign, than models that attempted to control for confounding variables. This opposite result arose from market identification and endogeneity problems. These were dealt with by controlling for regional markets, political environment, and the conflict, and instrumenting the change in labor with net migration, influenced during the war period by IDP movements.

Overall, these results have a major implication for labor reforms in Ukraine. While labor reforms are necessary it does appear, Ukraine has somewhat functioning labor markets in their post-Soviet economic environment. So, while reform may be necessary, the situation may not be as dire as it could have been.

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Appendix 1: Nabor force ~ wage 2SLS full result

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                   Wage   R-squared:                       0.059
Model:                            OLS   Adj. R-squared:                  0.057
Method:                 Least Squares   F-statistic:                     44.28
Date:                Thu, 07 May 2020   Prob (F-statistic):           5.70e-11
Time:                        13:16:57   Log-Likelihood:                -6272.5
No. Observations:                 713   AIC:                         1.255e+04
Df Residuals:                     711   BIC:                         1.256e+04
Df Model:                           1
Covariance Type:            nonrobust
===============================================================================
                  coef    std err          t      P>|t|      [0.025      0.975]
-------------------------------------------------------------------------------
Intercept    2785.8896    145.034     19.208      0.000    2501.143    3070.636
Labor_Force     1.1773      0.177      6.654      0.000       0.830       1.525

                        First Stage Regression Results
==============================================================================
Dep. Variable:            Labor_Force   R-squared:                       0.154
Model:                            OLS   Adj. R-squared:                  0.153
Method:                 Least Squares   F-statistic:                     129.2
Date:                Thu, 07 May 2020   Prob (F-statistic):           1.25e-27
Time:                        13:16:57   Log-Likelihood:                -5106.8
No. Observations:                 713   AIC:                         1.022e+04
Df Residuals:                     711   BIC:                         1.023e+04
Df Model:                           1
Covariance Type:            nonrobust
=================================================================================
                    coef    std err          t      P>|t|      [0.025      0.975]
---------------------------------------------------------------------------------
Intercept       730.6878     11.786     61.996      0.000     707.548     753.827
Net_Migration     0.1640      0.014     11.367      0.000       0.136       0.192


                       Second Stage Regression Results
==============================================================================
Dep. Variable:                   Wage   R-squared:                       0.053
Model:                            OLS   Adj. R-squared:                  0.051
Method:                 Least Squares   F-statistic:                     39.58
Date:                Thu, 07 May 2020   Prob (F-statistic):           5.51e-10
Time:                        13:16:57   Log-Likelihood:                -6274.7
No. Observations:                 713   AIC:                         1.255e+04
Df Residuals:                     711   BIC:                         1.256e+04
Df Model:                           1
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
Intercept   1539.8062    343.040      4.489      0.000     866.313    2213.299
PX             2.8473      0.453      6.291      0.000       1.959       3.736
```

Appendix 2: Labor force ~ unemployment 2SLS full result

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                            OLS Regression Results
==============================================================================
Dep. Variable:             Unemployed   R-squared:                       0.719
Model:                            OLS   Adj. R-squared:                  0.719
Method:                 Least Squares   F-statistic:                     1819.
Date:                Thu, 07 May 2020   Prob (F-statistic):         3.64e-198
Time:                        13:20:26   Log-Likelihood:                -2717.9
No. Observations:                 713   AIC:                             5440.
Df Residuals:                     711   BIC:                             5449.
Df Model:                           1
Covariance Type:            nonrobust
===============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
-------------------------------------------------------------------------------
Intercept     23.9172      0.992     24.120      0.000      21.970      25.864
Labor_Force    0.0516      0.001     42.653      0.000       0.049       0.054

                          First Stage Regression Results
==============================================================================
Dep. Variable:            Labor_Force   R-squared:                       0.154
Model:                            OLS   Adj. R-squared:                  0.153
Method:                 Least Squares   F-statistic:                     129.2
Date:                Thu, 07 May 2020   Prob (F-statistic):           1.25e-27
Time:                        13:20:26   Log-Likelihood:                -5106.8
No. Observations:                 713   AIC:                         1.022e+04
Df Residuals:                     711   BIC:                         1.023e+04
Df Model:                           1
Covariance Type:            nonrobust
=================================================================================
                   coef    std err          t      P>|t|      [0.025      0.975]
---------------------------------------------------------------------------------
Intercept      730.6878     11.786     61.996      0.000     707.548     753.827
Net_Migration    0.1640      0.014     11.367      0.000       0.136       0.192

                          Second Stage Regression Results
==============================================================================
Dep. Variable:             Unemployed   R-squared:                       0.065
Model:                            OLS   Adj. R-squared:                  0.064
Method:                 Least Squares   F-statistic:                     49.80
Date:                Thu, 07 May 2020   Prob (F-statistic):           4.05e-12
Time:                        13:20:26   Log-Likelihood:                -3146.3
No. Observations:                 713   AIC:                             6297.
Df Residuals:                     711   BIC:                             6306.
Df Model:                           1
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
Intercept     32.7955      4.264      7.691      0.000      24.424      41.167
PX             0.0397      0.006      7.057      0.000       0.029       0.051
```

Appendix 3: Labor force ~ wage 2SLS full result

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                 w_diff   R-squared:                       0.844
Model:                            OLS   Adj. R-squared:                  0.839
Method:                 Least Squares   F-statistic:                     155.0
Date:                Thu, 07 May 2020   Prob (F-statistic):          1.13e-258
Time:                        13:04:49   Log-Likelihood:                -5284.4
No. Observations:                 713   AIC:                         1.062e+04
Df Residuals:                     688   BIC:                         1.073e+04
Df Model:                          24
Covariance Type:            nonrobust
========================================================================================
                      coef    std err          t      P>|t|      [0.025      0.975]
----------------------------------------------------------------------------------------
lf_diff             3.9943      0.623      6.409      0.000       2.771       5.218
Conflict:lf_diff    0.7973      0.073     10.951      0.000       0.654       0.940
Poroshenko_14     -18.0154     10.563     -1.705      0.089     -38.756       2.725
Regional FX          Yes

                            First Stage Regression Results
==============================================================================
Dep. Variable:                lf_diff   R-squared:                       0.997
Model:                            OLS   Adj. R-squared:                  0.997
Method:                 Least Squares   F-statistic:                     9198.
Date:                Thu, 07 May 2020   Prob (F-statistic):               0.00
Time:                        13:04:49   Log-Likelihood:                -3340.5
No. Observations:                 713   AIC:                             6729.
Df Residuals:                     689   BIC:                             6839.
Df Model:                          23
Covariance Type:            nonrobust
=======================================================================================
                     coef    std err          t      P>|t|      [0.025      0.975]
---------------------------------------------------------------------------------------
Intercept      -1301.0111      7.191   -180.918      0.000   -1315.130   -1286.892
Net_Migration      0.0025      0.001      1.701      0.089      -0.000       0.005
Poroshenko_14     36.6976      0.194    189.414      0.000      36.317      37.078
Regional FX          Yes


Dep. Variable:              Second Stage Regression Results
==============================================================================
Dep. Variable:                 w_diff   R-squared:                       0.834
Model:                            OLS   Adj. R-squared:                  0.829
Method:                 Least Squares   F-statistic:                     144.5
Date:                Thu, 07 May 2020   Prob (F-statistic):          6.34e-250
Time:                        13:04:49   Log-Likelihood:                -5305.4
No. Observations:                 713   AIC:                         1.066e+04
Df Residuals:                     688   BIC:                         1.078e+04
Df Model:                          24
Covariance Type:            nonrobust
====================================================================================
                  coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------------
PX            -24.1208      9.259     -2.605      0.009     -42.301      -5.941
Conflict:PX     0.5847      0.069      8.534      0.000       0.450       0.719
Poroshenko_14 446.7552    152.494      2.930      0.004     147.346     746.165
Regional FX      Yes
```

Appendix 4: Labor force ~ unemployment 2SLS full result

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                 u_diff   R-squared:                       0.891
Model:                            OLS   Adj. R-squared:                  0.888
Method:                 Least Squares   F-statistic:                     235.1
Date:                Thu, 07 May 2020   Prob (F-statistic):         1.99e-312
Time:                        13:10:48   Log-Likelihood:                -2638.9
No. Observations:                 713   AIC:                             5328.
Df Residuals:                     688   BIC:                             5442.
Df Model:                          24
Covariance Type:            nonrobust
==================================================================================
                      coef    std err          t      P>|t|      [0.025      0.975]
----------------------------------------------------------------------------------
lf_diff            -0.1065      0.015     -6.984      0.000      -0.136      -0.077
Conflict:lf_diff   -0.0037      0.002     -2.104      0.036      -0.007      -0.000
Poroshenko_14       2.6662      0.258     10.315      0.000       2.159       3.174
Regional FX          Yes

                          First Stage Regression Results
==============================================================================
Dep. Variable:                lf_diff   R-squared:                       0.997
Model:                            OLS   Adj. R-squared:                  0.997
Method:                 Least Squares   F-statistic:                     9198.
Date:                Thu, 07 May 2020   Prob (F-statistic):               0.00
Time:                        13:10:48   Log-Likelihood:                -3340.5
No. Observations:                 713   AIC:                             6729.
Df Residuals:                     689   BIC:                             6839.
Df Model:                          23
Covariance Type:            nonrobust
=================================================================================
                    coef    std err          t      P>|t|      [0.025      0.975]
---------------------------------------------------------------------------------
Intercept     -1301.0111      7.191   -180.918      0.000   -1315.130   -1286.892
Net_Migration     0.0025      0.001      1.701      0.089      -0.000       0.005
Poroshenko_14    36.6976      0.194    189.414      0.000      36.317      37.078
Regional FX          Yes
                         Second Stage Regression Results
==============================================================================
Dep. Variable:                 u_diff   R-squared:                       0.884
Model:                            OLS   Adj. R-squared:                  0.880
Method:                 Least Squares   F-statistic:                     218.1
Date:                Thu, 07 May 2020   Prob (F-statistic):         1.63e-302
Time:                        13:10:48   Log-Likelihood:                -2662.7
No. Observations:                 713   AIC:                             5375.
Df Residuals:                     688   BIC:                             5490.
Df Model:                          24
Covariance Type:            nonrobust
=================================================================================
                    coef    std err          t      P>|t|      [0.025      0.975]
---------------------------------------------------------------------------------
PX               -0.2246      0.227     -0.988      0.324      -0.671       0.222
Conflict:PX       0.0012      0.002      0.697      0.486      -0.002       0.004
Poroshenko_14     4.5695      3.746      1.220      0.223      -2.785      11.924
Regional FX          Yes
```