Political Uncertainty, FDI, and Trade in Intermediate Goods: Evidence From Ukrainian Firms

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Abstract

In this paper, we explore the effects of uncertainty on firm performance and introduce a new method to measure uncertainty using quantitative text analysis. We extend a theoretical model with heterogeneous firms and sunk investments to derive hypotheses about the impact of trade policy uncertainty (TPU) on firm-specific investment and firm's decision to trade intermediate goods. We look at Ukraine's trade relations with EU and Russia to measure TPU and to test our predictions. Ukrainian firms faced considerable uncertainty with regards to two mutually exclusive trade policies: the conclusion of a free trade agreement with the European Union (EU FTA) or a customs union with Russia (RU CU). Using firm-product level data of Ukrainian manufacturing firms between 2003 and 2013, we find a substantive increase in firm-level FDI inflows and imported intermediate goods from EU countries and a decrease in FDI from the Customs Union, once uncertainty with regards to the EU FTA is reduced. Moreover, more protected goods respond stronger to a reduction in TPU. The novel measure of uncertainty can be easily applied to other cases where governments face multiple mutually exclusive policy options.

Keywords: trade policy, uncertainty, intensive margin, intermediate inputs, FDI, machine learning

JEL Classification: C55, D81, F12, F14

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1 Introduction

Stability of policies is crucial for firms to take sensible, long-term decisions. The World Bank recently warned that the contemporary rise in trade policy uncertainty (TPU) caused by anti-free trade rhetoric, particularly in the United States, could seriously endanger world trade and productivity growth (Donnan, 2017). Policy uncertainty and volatility matters for international trade because firms' decisions to export, import, and upgrade technology often involves large ex ante (sunk) investment decisions. When there is a chance that policies can be reversed, firms might delay necessary sunk investment, leading to lower trade and poor productivity. In the international trade literature, researchers have long recognized the role of demand uncertainty, its relationships with various trade policies, and their welfare implications (Fishelson and Flatters, 1975; Helpman et al., 1978), as well as the effects of uncertainty on dumping- and anti-dumping policies (Hillman and Katz, 1986; Falvey and Lloyd, 1991). Another strand of research deals with the reduction of uncertainty via tariff bindings (Francois and Martin, 2004) and free trade agreements (FTA, see for example Limao and Tovar, 2011).[1] Uncertainty has also been a major theme in macroeconomics (Bernanke, 1983; Dixit, 1989), industrial organization (Bloom et al., 2007), research on the design of international institutions (Rosendorff and Milner, 2001), and work on time-inconsistency (Kydland and Prescott, 1977).

Recently, the concept of uncertainty has gained renewed attention in the international trade literature (Handley, 2014; Handley and Limao, 2015; Limao and Maggi, 2015; Feng et al., 2017), connecting former research to models of heterogeneous firms (Melitz, 2003; Helpman et al., 2004). Handley (2014) focuses on WTO tariff bindings as means to attenuate TPU and increase product-level exports (see also Osnago et al., 2015). Limao and Maggi (2015) look at the uncertainty-reducing effect of FTA. At the firm-level, Handley and Limao (2015) use the case of Portugal's accession to the EEC as an uncertainty-reducing commitment, increasing firm export entries and sales. Feng et al. (2017) show that China's WTO accession as TPU reducing commitment increased Chinese firm export entries to the EU and the US, while Liu and Ma (2017) demonstrate that it encourages firm-level innovation in the form of patent applications.

What is missing from existing research is firm-level evidence on the impact of TPU on firm-level foreign direct investment (FDI) and intensive margins of trade, as well as more widely applicable and encompassing measures of uncertainty. First, even though the connection between investment and uncertainty is central to the theoretical literature, we are not aware of any studies

[1] For instance, Manger and Shadlen (2014) find that FTA 'lock in' preferential market access for developing countries since Generalized System of Preferences (GSP) tariffs can be unilaterally suspended, and Groppo and Piermartini (2014, p.1) estimate that WTO bindings "significantly reduce the probability of a tariff increase, even when the bound tariff is above the MFN applied rate".

looking at the effect of uncertainty on firm-level foreign direct investment (FDI). Second, while the extensive margin of trade, in particular exports, have been studied in abundance, we focus on the intensive margin, which has been ignored so far.[2] Finally, current work mostly uses quite specific measures of uncertainty such as the difference between MFN and bound tariffs. This measure cannot be applied to non-tariff barriers or more general changes in policies (i.e. labor market regulations, environmental standards, or financial regulations) and does not reflect dynamic changes that occur in higher frequencies (i.e. changes in expectations). Furthermore, researchers might still want to evaluate the impact of trade-policy-induced uncertainty when barriers to trade are not publicly available, for instance in the case of many developing and least developed countries, and for interesting historical cases for which tariff data is not available. Therefore, we suggest a quantitative text analysis approach to measurement of uncertainty as a useful complement to more traditional methods.

We improve on existing work in three ways. First, we extend the TPU heterogeneous firm model with monopolistic competition of Handley and Limao (2015) by introducing an additional decision on the choice of intermediate inputs. These intermediate goods can be sourced from domestic and foreign suppliers, with wider choice increasing productivity (Ethier, 1982), but importing requires irreversible sunk investments.[3] The connection between TPU and imported intermediate inputs is especially important, since these inputs have been shown to improve firm productivity (Amiti and Konings, 2007; Halpern et al., 2015; Ramanarayanan, 2017), which in turn impacts intensive margins of export.

Second, we empirically investigate both this link between changes in TPU and imports of intermediate inputs, as well as the the impact of TPU on firm-level FDI. We test our model predictions using Ukrainian manufacturing census data on firm-level trade and FDI between 2003 and 2013. Ukraine is a well-suited case to investigate the role of TPU because she faced an unusually volatile trade policy with regards to both Russia and the EU over the last two decades, being torn between two *mutually exclusive* policy options: an FTA with the EU (EU FTA) or a Customs Union with Russia (RU CU) (Hoekman et al., 2014). We use a particular definition of trade policy uncertainty: we conceptualize TPU as the probability of Ukraine signing either the EU FTA or joining the CU with Russia. In this binary decision, each of those two options implies increased uncertainty with regards to the alternative policy because both policies could not have been implemented at the same time. Being part of the RU CU would have made it impossible for Ukraine to negotiate an FTA with the EU on its own due to the common external tariff, and joining the RU CU after concluding

[2]The exception is the theoretical treatment by Novy and Taylor (2014), but see footnote 3 below.

[3]This is similar to the TPU model with intermediate inputs by Novy and Taylor (2014), but contrary to their paper, we emphasize the heterogeneity across firms, and the technology upgrading channel for intermediate goods.

the EU FTA was impossible due to incompatibility of the RU CU tariff structure with the EU FTA trade regime and with the WTO commitments of Ukraine. The shifts in TPU between the RU CU and the EU FTA were difficult to predict for firms and driven by exogenous foreign policies of the EU and Russia. Moreover, the decision between closer economic ties with the West (EU) or the East (Russia) resulted in multiple political turnovers in Ukraine (Earle and Gehlbach, 2015), terminating in the Russian annexation of Crimea in early 2014.

Finally, we provide a new measure of TPU by applying quantitative text analysis tools. We use so-called structural topic models (Roberts et al., 2014) to analyze a large collection of over 2000 press news releases on Ukrainian economic policy to approximate the uncertainty between the EU FTA and the RU CU. In that respect, our approach is similar to that by Baker et al. (2016). However, we do not purposely select keywords such as 'uncertainty' but use a method which requires less decisions by the researcher. This approach is almost fully automated and can be easily applied to a broad range of other cases involving multiple, mutual exclusive policies. Decisions of joining and exiting a customs union are examples, where this measure can be used to study uncertainty generated by trade policy. Our measure can also be used to study uncertainty-inducing non-trade policies, such as the decision of governments to join military alliances, as well the study of trade policy choices in least developed countries, where reliable tariff data and effectiveness of formal institutions are scarce.

Our results underline the importance of TPU for firm-level trade and investment. We find that a reduction in TPU has a positive and sizable effect on FDI and import decisions. Conversely, a reduction in the probability of joining the RU CU is associated with more imports from EU countries. This is because the CU would have increased Ukrainian MFN tariffs compared to the status quo, whereas the EU FTA left MFN tariffs untouched.[4] We also find that imports of products that are more protected in the CU relative to Ukrainian MFN tariffs expand more once TPU is reduced. According to our results, full elimination of TPU (signing EU FTA), would increase imports to Ukraine from EU countries by 13.4 percent, while tariff reduction would increase imports by 5.3 percent. Finally, we show that FDI strongly responds to changes in TPU that are consistent with our model. FDI from EU responds positively to an increase in the likelihood of signing an EU FTA and responds negatively to an increase in the likelihood of joining CU. The effects for FDI from the CU are exactly opposite, albeit not as strong. Full elimination of TPU by signing the EU

[4] Russia threatened to withdraw from the free trade agreement with Ukraine, apply MFN tariffs, and impose some arbitrary bans on sensitive items of Ukrainian imports to Russia (milk, cheese, chocolate, railway carriages), but as previous cases related to the Eastern European countries joining EU (i.e Estonia, Poland) demonstrated, those sanctions were short-lived. While trade policy retaliation from Moscow might have been credible, firms could not reasonably believe that a decision to join EU FTA could lead to a full-scale conflict between Ukraine and Russia, annexation of Crimea, and war in the Eastern Ukraine.

FTA would increase FDI from EU by 34 percent. Our findings indicate that swings in the political viability of trade policies have sizable impacts on firms' decisions to trade.[5] Given the important role of intermediate inputs and FDI for technological upgrading of firms, our findings also have implications for the prospects of firms in developing countries.

Building on the theoretical work by Handley and Limao (2015), the next section outlines our monopolistic competition model with heterogeneous firms and trade policy uncertainty. The third section introduces the reader to the trade policy context of Ukraine and discusses methodology and data sources, focusing on our TPU measure. Section four describes the results of our empirical models. The last section concludes and states avenues for further research and possible applications of our TPU measure.

2 Model

As a point of departure we use a partial equilibrium model of monopolistic competition with heterogeneous firms, facing a costly and irreversible export decision and uncertainty in the foreign demand (Handley and Limao, 2015). However, we add two important changes. First, we modify the trade uncertainty process to account for a binary and mutually exclusive choice between two policy alternatives. In our case, an increase in uncertainty of exporting to EU is represented by a higher probability of joining RU CU. Likewise, uncertainty of exporting to the CU increases in a probability of signing EU FTA. Second, we incorporate a decision about imports of intermediate goods into the production process. Assuming that this decision involves costly and irreversible investment, eventually requiring to attract foreign direct investment, we show that uncertainty negatively influences imports and FDI.

An extensive literature shows that the purchase of imported intermediate goods and inward foreign direct investment are important mechanisms for the increase in total factor productivity (TFP). Amiti and Konings (2007) disentangle the effect of trade liberalization on productivity into output competition vs. input liberalization effects. The theoretical underpinnings of the input tariff liberalization effect on productivity are divided into static and dynamic gains. The static gains include gains from increased variety of inputs (Ethier, 1982; Markusen, 1989) and gains from better quality imported inputs (Hallak and Sivadasan, 2013). The dynamic gains come from learning from importing (Grossman and Helpman, 1991).

A recent empirical literature compares the relative importance of these gains. Halpern et al. (2015) demonstrate that gains from variety attributed to two-third of productivity gains, while

[5] These findings also contradict existing research on the impact of those swings on aggregate trade and other economic indicators (Davis and Meunier, 2011).

one-third came from better quality of imported inputs. Zhang (2017) further finds that importing increases productivity in the next period by 0.5-5.8 %. Finally, Ramanarayanan (2017) adds sunk costs with irreversibility to the model. Matching the model predictions to Chilean plant level data, introduction of irreversible costs of importing improves the model fit by about two thirds. We use these findings to model the impact of uncertainty on imports.

Basic model of exporting without uncertainty and without intermediate inputs

An exporting firm from a small open economy produces a variety ω. The firm is small relative to the market size of differentiated varieties in importing countries (more generally, trade blocks or customs unions) and "believes" that it is too small to impact aggregate statistics. Assuming a standard constant elasticity of substitution utility function across varieties, the firm is facing demand

$$q(\omega) = p(\omega)^{-\sigma} E \times P^{\sigma-1} \tag{1}$$

where σ is the elasticity of substitution across varieties, $p(\omega)$ is price of variety ω, E is the total expenditures on goods in the differentiated sector, and $P = \left(\int_{\omega\in\Omega} p(\omega)^{1-\sigma} d\omega\right)^{1/(1-\sigma)}$ is the price index, where Ω is the set of available varieties. We further assume that σ is common across all markets. In order to start production the firm has to pay a fixed cost and learn its marginal cost is $c(\omega)$, which is drawn from a known distribution defined over $(0,\infty)$. Once the firm learn its marginal cost, it decides whether to produce or not.

To enter a new export market j, the firm incurs an irreversible cost, I_{EX}, which is pair-specific and can not be applied to exporting to another country. If the firm exports, there is an exogenous probability of exporting continuation, $\beta < 1$. An exporting firm is subject to a tariff $\tau^j_{EX,s} \geq 1$, which depends on the trade policy state, s. Given market conditions and trade policy state, this uniquely determines the profitability cutoff of the marginal exporting firm which is given by

$$c^j_{EX,s} = \left(\frac{(1-\beta)I_{EX}}{a^j_s}\right)^{1/(1-\sigma)}. \tag{2}$$

where $a^j_s = (\tau^j_{EX,s}\sigma)^{-\sigma}[(\sigma-1)P]^{\sigma-1}E$.

Trade policy uncertainty

The small open economy trades with both the EU and CU. The three feasible policy states are a free trade agreement with the EU (EU FTA), the status quo policy (MFN), and the customs union membership (RU CU). In the case of the EU FTA, exporters from the small open economy face the tariff schedule $\tau_{EX,FTA} = \{\tau^{EU}_{EX,FTA} = 0, \tau^{CU}_{EX,FTA}\}$, which refers to a zero import tariff schedule imposed by EU and MFN import tariffs imposed by the CU.[6] The status quo trade policy means that the EU MFN tariff rates are applied to exports to the EU and zero tariffs to exports to the CU: $\tau_{EX,MFN} = \{\tau^{EU}_{EX,MFN}, \tau^{CU}_{EX,MFN} = 0\}$.[7] Finally, in the case of the CU, the tariff schedule is $\tau_{EX,CU} = \{\tau^{EU}_{EX,CU}, \tau^{CU}_{EX,CU} = 0\}$. Even though the EU applies the same MFN tariff rates to both Ukraine and the CU countries, by joining the CU Ukraine would worsen access of its firms to the EU countries ($\tau^{EU}_{EX,MFN} \leq \tau^{EU}_{EX,CU}$) for two reasons. First, current WTO binding import tariffs of Ukraine are lower than CU applied import tariffs. Therefore, if Ukraine joined the CU and adjusted its import tariffs to the CU levels, it would violate its WTO commitments and trigger a lengthy and unpredictable process of renegotiating its bilateral trade relationships with all WTO members, including EU countries. Second, it would have to harmonize its technical standards and phytosanitary norms with the CU norms, which differ substantially from the EU standards, making it harder for Ukrainian firms to export to the EU. The trade policy states for exports to the EU and the CU are summarized in columns (1) and (2) of Table 1.

Table 1: Ukrainian tariffs for export of final goods to EU and CU

State, s	Export to EU (1)	Export to CU (2)	Imports from EU (3)	Imports from CU (4)
EU FTA	0	$\tau^{CU}_{EX,MFN}$	0	$\tau^{UKR}_{IM,MFN}$
MFN	$\tau^{EU}_{EX,MFN}$	0[b)]	$\tau^{UKR}_{IM,MFN}$	0[c)]
RU CU	$\tau^{EU}_{EX,CU} \geq \tau^{EU}_{EX,MFN}$ [a)]	0	$\tau^{UKR}_{IM,CU} > \tau^{UKR}_{IM,MFN}$	0

[a)] May be higher due to potential WTO disputes and non-tariff measures
[b)] There are some important exceptions
[c)] Some important restrictions apply

Columns (3) and (4) of the table present import tariffs that would be imposed on domestic producers importing from the EU and CU under different policy states. In the EU FTA state, the import tariffs for goods from EU countries equal zero, $\tau^{UKR}_{IM,FTA} = 0$, and for goods from CU equal

[6] It was repeatedly mentioned by the CU representatives that if Ukraine signed EU FTA, it would lose its free trade status with the CU countries. However, one might argue that such a threat was not considered as credible before 2014. Moreover, the EU FTA is compatible with its free trade with the CU countries. Therefore, it is not clear whether Ukrainian firms attached high probability to a scenario where CU withdrew from the free trade with Ukraine.

[7] Until recently, the Ukrainian exports to Russia were mostly tariff free with several exceptions. At the same time, Russia frequently introduced non-tariff measures that essentially blocked Ukrainian exports to Russia.

Ukrainian MFN import rates, $\tau^{UKR}_{IM,MFN} > 0$. In the MFN state, the tariff rates for goods from EU are positive $\tau^{UKR}_{IM,MFN} > 0$, and hence, larger than in the FTA state. In the CU state, the import tariffs for imports from EU are $\tau^{UKR}_{IM,CU} > \tau^{UKR}_{IM,MFN} > 0$.[8] For imports from the CU countries, Ukrainian tariffs are zero for both MFN and CU states.

The state of the trade policy is a Markov process with a transition probability matrix

$$\Lambda = \begin{pmatrix} \Lambda_{FTA} \\ \Lambda_{MFN} \\ \Lambda_{CU} \end{pmatrix} = \begin{pmatrix} 1 & 0 & 0 \\ p_{EU} & p_{MFN} & p_{CU} \\ 0 & 0 & 1 \end{pmatrix} \tag{3}$$

with $p_{EU} + p_{MFN} + p_{CU} = 1$. The small open economy starts in the MFN state. Once the small open economy moves to either state FTA or CU, it remains in that state indefinitely. Also, if we rank policy states according to the ease of access to the EU markets as $CU \preceq MFN \preceq FTA$, Λ_{FTA} stochastically dominates Λ_{MFN}, which in turn stochastically dominates Λ_{CU}.

Exporting under uncertainty

If the future is uncertain, with the source of uncertainty generated by the state of the trade policy, the firm has two decisions to make. First, it decides on whether to export or not. We assume that the firm is risk neutral, so it cares only about expected value.[9] We also assume that the transition probability matrix (3) is common knowledge, shared by all firms. Second, the firm decides on the optimal timing to start exporting. As shown by Handley and Limao (2015) , the cutoff is given by

$$\tilde{c}^{EU}_{EX,MFN} = \left(\frac{1 - \beta(1 - p_{CU})}{1 - \beta(1 - \frac{a_{CU}}{a_{MFN}} p_{CU})} \right)^{\frac{1}{1-\sigma}} \times c^{EU}_{EX,MFN} \tag{4}$$

There is no effect of uncertainty on extensive margins of exports to EU if $p_{CU} = 0$. An increase in the probability of switching from MFN to the CU, which is the only probability that matters in this case, lowers the marginal cost cutoff, making it tougher to enter the EU markets. The effect is stronger the smaller the ratio $a_{CU}/a_{MFN} = (\tau^{EU}_{EX,CU}/\tau^{EU}_{EX,MFN})^{-\sigma}$ is. On the other hand, if $\tau^{EU}_{EX,CU} = \tau^{EU}_{EX,MFN}$, there is no effect of uncertainty on exports to EU for any level of p_{CU}.

To sum up, a reduction in the probability of joining the RU CU would increase exports to EU if firms perceive that joining the Customs Union increases EU tariffs applied against Ukrainian

[8] This follows from the fact that the CU tariffs are higher than the Ukrainian tariffs. We discuss this issue in details in the data section.

[9] It might be an interesting extension to consider a risk averse firm, which imposes different modifications of the objective function, and the firm faces a trade off of lower expected return in order to reduce the risk of an adverse outcome.

exports and would have have no effect if firms perceive EU policy to remain unchanged.

Imported inputs and productivity

Now, consider a firm that may source its inputs domestically or import them from the EU or CU. Instead of assuming exogenously given marginal cost, we introduce the following production function

$$q = \varphi L^{\alpha_L} K^{\alpha_K} M^{\alpha_M} \tag{5}$$

where q is output, φ is productivity, L is labor, K is capital, and M is composite intermediate input. We assume that productivity is firm specific and drawn from a known distribution function defined over $(0,\infty)$. We also assume a constantreturns to scale, $\alpha_L + \alpha_K + \alpha_M = 1$.

Further suppose that intermediate inputs are a composite good, such that

$$M = \left(X_D^{\frac{\theta-1}{\theta}} + X_F^{\frac{\theta-1}{\theta}} \right)^{\frac{\theta}{\theta-1}}$$

where X_D is a domestic intermediate input, X_F is an imported intermediate input, and $\theta > 1$ is elasticity of substitution across domestic and foreign intermediate inputs. Further, there are varieties of domestic and foreign suppliers of intermediate inputs given by $X_D = [\sum^{n_D} x_D^{\varepsilon}]^{1/\varepsilon}$and $X_F = [\sum^{n_F} x_F^{\varepsilon}]^{1/\varepsilon}$, where $\sigma_\varepsilon = 1/(1-\varepsilon)$ is elasticity of substitution across inputs and $0 < \varepsilon < 1$.

We assume that factor prices w_L, w_K, w_D, and w_F are exogenous. To incorporate a foreign intermediate input into production process, a firm incurs irreversible investment I_{IM} per foreign variety, which is partner-specific and can not be recovered by switching to another intermediate good supplier. In addition, there is an ad-valorem tariff, $\tau_{IM,s}$ that is paid by importers. Solving cost minimization problem yields

$$c(\varphi) = \frac{1}{\varphi} \left(\frac{w_L}{\alpha_L} \right)^{\alpha_L} \left(\frac{w_K}{\alpha_K} \right)^{\alpha_K} \left(\frac{P_M}{\alpha_M} \right)^{\alpha_M}$$

where $P_M = \left(n_F (\tau_s^{IM} w_F)^{1-\theta} + n_D w_D^{1-\theta} \right)^{\frac{1}{1-\theta}}$if the firm imports and $P_M = (n_D)^{1/(1-\theta)} w_D$ if it uses domestic inputs only. Given a productivity level φ, the ratio of the unit costs for a firm with foreign inputs c_{IM} and a firm with domestic inputs c is given by

$$\mu(\tau_{IM,s}, n_D, n_F) = \frac{c_{IM}}{c} = \left[1 + \frac{n_F}{n_D} \left(\frac{w_D}{\tau_{IM,s} w_F} \right)^{\theta-1} \right]^{\frac{-\alpha_M}{\theta-1}} \leq 1 \tag{6}$$

There are two sources of cost advantage of importing firms. First, prices may not be fully aligned and hence, imported inputs may provide an advantage if $\tau_s^{IM} w_F < w_D$.[10] Second, even if $\tau_s^{IM} w_F = w_D$, the importing firm has a cost advantage due to imperfect substitutability of inputs: $c_{IM} = c \times (1 + \frac{n_F}{n_D})^{\frac{-\alpha_M}{\theta-1}} = c \times \mu$. If $n_F \gg n_D$, which is very likely to be the case for a small open economy, then $c_{IM} \ll c$.

Consider an increase in import tariffs from $\tau_{IM,MFN}^{UKR}$ to $\tau_{IM,CU}^{UKR}$. Keeping number of foreign and domestic suppliers fixed, this scenario would result in an increase in the unit cost of an importing firm

$$\ln c_{IM,CU} - \ln c_{IM,MFN} = \frac{\alpha_M}{\theta - 1} \times \frac{n_F}{n_D} \left(\frac{w_D}{w_F}\right)^{\theta-1} \left[\left(\frac{1}{\tau_{IM,MFN}^{UKR}}\right)^{\theta-1} - \left(\frac{1}{\tau_{IM,CU}^{UKR}}\right)^{\theta-1} \right] \tag{7}$$

Exporting with intermediate imported inputs

Let us denote $c_{IM,s} = \mu(\tau_{IM,s}, n_{D,s}, n_{F,s}) \times c = \mu_s c$, where $0 < \mu \leq 1$ and $\frac{\partial \mu}{\partial \tau_s^{IM}} > 0$. In addition we denote $\tilde{I}_{IM} = I_{IM} \times n_F$. Under certainty a firm imports intermediate inputs if

$$c \leq c_{IM,s}^{j} = \left[\frac{(1-\beta)\tilde{I}_{IM}}{a_s^j(\mu^{1-\sigma} - 1)} \right]^{\frac{1}{1-\sigma}} \tag{8}$$

Comparing (8) with (2), all exporting firms would invest in imported inputs if $I_{EX} > \tilde{I}_{IM}(\mu^{1-\sigma} - 1)$. However if $I_{EX} \leq \tilde{I}_{IM}(\mu^{1-\sigma} - 1)$, only a subset of exporting firms invests in intermediate inputs, and the two cutoffs are related as given by

$$c_{IM,s}^{j} = c_{EX,s}^{j} \times \left(\frac{\tilde{I}_{IM}}{I_{EX}}\right)^{\frac{1}{1-\sigma}} \times (\mu^{1-\sigma} - 1)^{\frac{1}{\sigma-1}}$$

[10]Another interpretation is that imported goods may provide an advantage because they are cheaper in quality adjusted price.

Importing with uncertainty

We consider the case when there is uncertainty in import tariffs, but no uncertainty in export tariffs, $a_s^j = a^j$.[11] In order to optimally chose mix of inputs, a firm solves the following stopping problem

$$\Pi_s = \max\{\Delta\Pi_s^e, \beta E_s \Pi_{s'}\}$$

where $\Delta\Pi_s^e = \pi(a^j, \mu_s \times c) - \pi(a^j, c) + E_s \sum \beta^t [\pi(a^j, \mu_{s'} c) - \pi(a^j, c)]$. It is straightforward to demonstrate that similarly to the case with export uncertainty, there is a unique import cutoff threshold, which is lower under full certainty, and where reduction in p_{CU} leads to more imports of intermediate inputs. The relationship between import cutoff under certainty and under uncertainty is given by

$$\tilde{c}_{IM,MFN}^{EU} = \left(\frac{1 - \beta(1 - p_{CU})}{1 - \beta(1 - \left(\frac{\mu_{CU}^{1-\sigma} - 1}{\mu_{MFN}^{1-\sigma} - 1}\right) \times p_{CU})} \right)^{\frac{1}{1-\sigma}} \times c_{IM,MFN}^{EU} \tag{9}$$

If the use of imported inputs involves irreversible sunk costs, firms in the small open economy react to changes in TPU when considering to use imported intermediate inputs . Moreover, a reduction in TPU would stimulate companies to invest in technology upgrading, because the benefits of adopting new technologies are proportional to the (increased) revenues from exporting, while the costs are fixed (Bustos, 2011). The increased productivity, in turn, would lead to increase in exports on the intensive margin.

FDI and uncertainty

The previous analysis demonstrates that TPU reduction would stimulate companies to export and import, given there are substantial fixed costs of exporting and importing. The required investment may partially come from inflow of foreign direct investments. TPU reduction not only lowers uncertainty for domestic firms that consider exporting to EU and facilitates imports of intermediate inputs, it also encourages foreign multinational enterprises (MNE) to invest in local firms (FDI). For foreign investors from the EU, the effect of TPU reduction on investment would depend on the type of FDI. In the case of *vertical FDI*, lower TPU would stimulate more FDI because vertical investment depends on low trade barriers to ship intermediate goods to the small open economy

[11] This assumption can be relaxed to $a_{MFN} = a_{CU}$, meaning there is no possibility of fundamentals decline in some state of the future trade policy. We can also consider a model with uncertainty in export and import tariffs, which would not change our conclusions, but would considerably complicate discussion.

and processed outputs back to the source country. This would also be an important stimulus for off-shoring some tasks to the small open economy for companies from the EU (Grossman and Rossi-Hansberg, 2008).[12] For horizontal FDI in companies that serve the domestic market and perhaps other countries that have a free trade agreements with the small open economy, a reduction in TPU would make investment less attractive, because it would make it less risky to serve these markets by simply exporting.[13] In the next section we move to empirical evidence on the relationship between trade, FDI, and uncertainty.

3 Data and Empirics

Ukrainian Trade Policy vis-a-vis the EU and Russia

Since the fall of the Iron Curtain, Eastern European countries had to re-orient their foreign economic policies and sought either closer ties with the EU or the Russian Federation. By 2011, 12 former communist countries had joined the EU. Meanwhile, Russia pursued the Eurasian Economic Union (EAEU) since 2000, a customs union with Belarus and Kazakhstan. In 2003, Russian president Valdimir Putin officially invited Ukraine to join the customs union project, and publicly supported the pro-Russian candidate Victor Yanukovich in the Ukrainian presidential elections. However, Ukraine had already applied for EU membership in 1995, and most Ukrainian voters supported the Western-friendly candidate Victor Yushchenko.[14]

The Orange Revolution in 2004 resulted in a pro-EU government, and the WTO accession in 2008 further paved the way to negotiation of a free trade agreement with EU (Shepotylo and Vakhitov, 2015). In May 2009, the EU started the Eastern Partnership with the six ENP countries in order to "[...] create the necessary conditions to accelerate political association and further economic integration between the European Union and interested partner countries" (CoEU, 2009). In addition to free trade, the European Union offered broader Association Agreements (AA) which included political cooperation, but without the promise of future EU accession (Åslund, 2013). However, in 2010, Victor Yanukovich won the presidential elections promising to strengthen economic ties with Russia, while still following a two-tier trade strategy: "From his re-election in 2010 onward,

[12]Manger (2009) shows that vertical FDI has been a major motivation behind EU FTAs with developing countries.

[13]For instance, if tariff rates to export to Russia from EU are high, and the same rates to export from Ukraine are low, Ukraine can be targeted by the European MNEs for horizontal FDI in order to serve local and Russian markets.

[14]In 2003, the EU had launched the European Neighborhood Policy (ENP), which supported structural reforms in exchange for improved market access and liberalization of visa regimes(Cadier, 2014). ENP governs the EU's relations with 16 of the EU's closest Eastern and Southern Neighbors. To the South: Algeria, Egypt, Israel, Jordan, Lebanon, Libya, Morocco, Palestine, Syria and Tunisia and to the East: Armenia, Azerbaijan, Belarus, Georgia, Moldova and Ukraine. Russia takes part in Cross-Border Cooperation activities under the ENP and is not a part of the ENP as such. Source: `https://ec.europa.eu/neighbourhood-enlargement/neighbourhood/overview_en`

President Yanukovych had purportedly cultivated ambiguity on the geopolitical orientation of his country...neither by originally indicating his readiness to sign the AA nor by eventually rejecting it" (Cadier, 2014). His government continued negotiations on a deep and comprehensive free trade agreement with the EU (DC FTA) which was supposed to lower tariffs and Non-Tariff Barriers (NTBs) between Ukraine and the EU.

Moscow vehemently opposed both the DC FTA and the AA, because she viewed them as a threat to their customs union. Before the 2013 Eastern Partnership summit in Vilnius where the DC FTA was scheduled to be signed, Russia imposed import bans on major Ukrainian exports to Russia and threatened to withdraw from an existing bilateral FTA with Ukraine. Russia also promised to lower energy prices, and to provide financial assistance worth of 15 billion dollars if Yanukovich refused to sign the DC FTA. On 21 November 2013, Yanukovich finally refused to sign the EU DC FTA, which triggered a civil unrest that eventually overthrew the Yanukovich regime in January 2014. Since then, a newly elected Ukrainian government has strongly committed to the path of European integration. The FTA between the EU and Ukraine entered into force on January 1st 2016.

Firm level data

The firm level data come from statistical forms that all Ukrainian firms have to submit to Ukrstat, the State Statistical Service of Ukraine. Firm output is measured as total sales revenues net of excise and other indirect taxes; this measure comes from the Financial Results Statement. The same statement contains data on material costs, which is measured as the firm's expenditures on materials, supplies, and utilities. The Balance Sheet statements also contain data on the end-of-year value of fixed assets, which we use as our measure of capital endowment of each firm. Firm employment, which is reported along with the Balance Sheet statement, is measured as the full-time equivalent of the labor force, and calculated as the average number of employees weighted by their time involvement. We use this data to calculate important firm-level variables like employment and total factor productivity (TFP). The estimation methodology and main results are described in Shepotylo and Vakhitov (2015).

Foreign direct investment is reported quarterly and submitted to the Ukrstat by all firms with changes in their FDI stock within the previous quarter. The data contains information on firm i's current stock of FDI from country j at quarter-year t.

We limit our sample to manufacturing firms (Section D of NACE, Revision 1 of Statistical Classification of Economic Activities) in 2003-2013. The focus on manufacturing firms is driven by the following considerations. First, this section of economy is better described as monopolistically competitive, relative to mining and quarrying, where the market is oligopolistic with the dominance of a few companies producing more homogeneous goods, or utility companies where state regulation is strong. Second, productivity in manufacturing is better defined and more precisely measured then in services. Finally, manufacturing firms are more likely to use imports as intermediate inputs, unlike firms in some other sections of economy (i.e. firms in wholesale and retail trade import mostly to resell goods).

Exports and imports

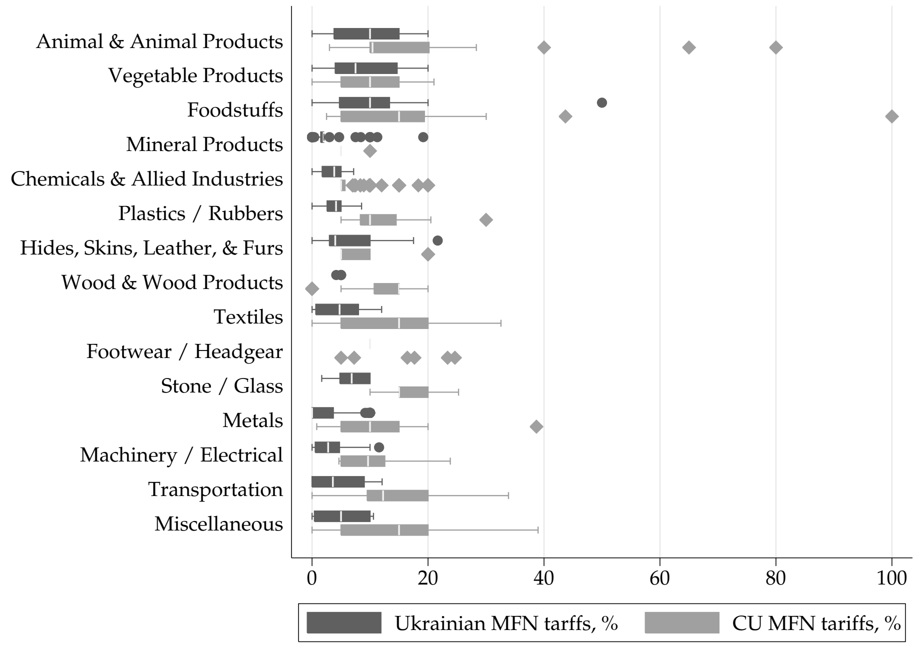
The transaction-level database of foreign trade in goods, collected by the Ukrainian Customs Service, is used for generating our export and import values. The data set provides comprehensive information on all export and import transactions at the firm level during a given year. It also contains information on the value and quantity of trade, country of origin as well as country of destination, and the product classification code at the four-digit level of the Harmonized System (HS-4). The comprehensive transaction level data set enables us to link firm-level exports and imports to MFN tariffs at the HS-4 level, which we describe in the following subsection.

Trade policy

One of our key predictions is that reduction in TPU has a larger impact on trade for products with higher MFN tariff rates. To understand what are the implications of Ukraine joining CU with Russia, Belarus, and Kazakhstan, it is important to emphasize that as a WTO member, Ukraine has accepted a multilateral schedule of binding tariff rates which is not compatible with the CU MFN tariff schedule. The data for the CU tariff policy come from Shepotylo and Tarr (2013), while the data for Ukrainian trade policy come from the TRAINS database. The applied MFN rates of Ukraine are very close to the binding rates, so in the analysis that follows, we compare the applied MFN rates of Ukraine and the CU.

Figure 1 illustrates the variation in tariff rates between Ukraine and the CU by product categories in 2012. The CU is more protective then Ukraine in all product categories, in particular in foodstuff, textiles, transportation, wood and wood products. If Ukraine were to join the CU in 2012, it would have increased its applied MFN rates for more than 90 percent of all product lines. The average increase would have been 6.50 percentage points. As outlined above, this would be a substantive increase in the levels of tariffs in the case of the CU. In contrast, the EU FTA would leave Ukraine's MFN tariffs untouched (but lower than CU tariffs) and set most of the tariffs vis-a-vis EU countries to zero.

Figure 1: Differences in applied MFN tariff rates between Ukraine and the RU CU in 2012



This graph illustrates differences in the distribution of applied MFN tariff rates between Ukraine and the CU. For each product category, a box represents the 25th to 75th percentile of the distribution of tariffs, a white stripe inside the box represents the median value, lower and upper ticks represent the lower and upper adjacent values, and diamonds indicate outlier. The figure illustrates that the CU MFN tariffs are higher than Ukraine's MFN tariffs in all product categories, particularly in foodstuff, transportation, textiles as well as wood and wood products.

Measuring Trade Policy Uncertainty

We conceptualize TPU as the probability of Ukraine signing either the EU FTA or joining the CU with Russia. In this binary decision, each of these policies means increased uncertainty with regards to the alternative, because both policies could not have been implemented at the same time. While the common external tariff of the RU CU would have made the conclusion of the EU FTA impossible, an FTA with the EU would have rendered the CU with Russia politically unfeasible and might have resulted in Russia imposing MFN tariffs on Ukrainian imports In order to measure TPU, we exploit automated (unsupervised) machine learning techniques for the analysis and classification of large-scale, unstructured collections of texts. We use these techniques in order to retrieve probabilities for the formation of a CU with Russia and the conclusion of a FTA with the EU from Ukrainian business news articles. A higher probability of EU FTA means a lower likelihood of the RU CU, and vice versa, as outlined in the theory section above.

Estimating Trade Policy Uncertainty from Texts using Topic Models

Our main source for measuring TPU consists of approximately 2200 news briefs from Ukraine Business Weekly (UBW). Operated by Interfax, UBW is a press release service which provides summaries of business and financial news in Ukraine. We choose UBW because it is available over a long period of time, from January 2003 to today, and it concerns business news only, which makes it more relevant to our investigation than daily newspapers. For measuring TPU from the articles, we use so-called "topic models", developed by computer scientists for the analysis and organization of large-scale collections of texts. Topic models analyze relative word occurrences in un-labeled documents in order to infer "themes" that run through them.[15] It is therefore crucial to understand that topics *are not defined ex ante* by the researcher, like in hand-coding of documents based on pre-defined dictionaries.[16]

A topic K is defined as a distribution over a fixed vocabulary V. The data generating process is as follows: we assume that documents (press releases) are created by K topics. Across documents, we first randomly choose a distribution over topics β_k. Each document is modeled as a distribution over K topics, θ_d. Within each document, words are generated by a two step process. First, for each word $z_{d,n}$, one draws a topic for that word from a multinomial distribution $z_{d,n} \sim Mult(\theta_d)$ (with $z_{d,n}$ indexing the topic assignment for the n-th word in document d). Second, an actual word $w_{d,n}$ is drawn from a distribution over the vocabulary $w_{d,n} \sim Mult(\beta_{z_{d,n}})$ where $\beta_{k,v}$ is the probability of drawing the v-th word in the vocabulary for topic k. The likelihood of a word for a given topic is then the probability of a topic within a given document times the probability of a term in the overall word distribution, $p(z_{d,n}) \cdot p(w_{d,n})$. This joint distribution of the latent and observed parameters (Blei et al., 2012) is formally given by

$$p(\beta_{1:K}, \theta_{1:D}, z_{1:D}, w_{1:D}) = \prod_{i=1}^{K} p(\beta_i) \prod_{d=1}^{D} p(\theta_d) \left(\prod_{n=1}^{N} p(z_{d,n}|\theta_d) p(w_{d,n}|\beta_{1:K}, z_{d,n}) \right).$$

Finally, the the model assume a Dirichlet prior for the topic proportions over documents d, so that $\theta_d \sim Dirichlet(\alpha)$ (Blei et al., 2003). This joint probability distribution can be used in order to calculate the topic posterior probabilities θ_d for each document. Higher posterior likelihoods of a topic means that a high proportion of terms in document is related to that topic. The intuition is that *documents* in a collection of documents contain multiple *topics* or themes. All documents in a collection are composed of the same topics, but they exhibit these topics in different proportions,

[15] These models have been successfully applied in both Political Science (Grimmer, 2010; Roberts et al., 2014) and Economics (Mueller and Rauh, 2016), and many more fields such as Genetics or Information Science (Blei, 2012).

[16] For a good description of the basics of dictionary-based text analysis see Neuendorf (2002, CH6). A well-known application of dictionary-based methods keywords representing left-right ideology in order to estimate scores of party positions using their election manifestos (Laver and Garry, 2000).

and words contribute to topics to differing degrees. Bigrams like "Association Agreement" or "Eastern Partnership" are related to the topic "EU-Ukraine FTA" , while terms like "customs union" or "EACU" would be related to the topic "Russia-Ukraine Customs Union". Topic models do not require any prior information about the text - only the number of topics K needs to be specified. We use *Structural topic models* (STMs) which allow the introduction of document-level covariates, in our case, the publication date, allow for topics to vary over time (Roberts et al., 2014).[17]

4 Empirical Results

TPU

Figure (2) shows the $K = 10$ topics and the five terms mostly associated with them.[18] The x-axis shows the overall topic proportions across all articles from all 10 topics, which sum up to 1. One can clearly identify the two topics which we are interested in: *Topic 1* is about Ukraine approaching the EU, about the Eastern Partnership process and the Association Agreement ("easternpartnership", "euukrain", "associationagr"). *Topic 8* is about the Ukraine joining the CU with Russia. Documents with high proportions of this topic use terms like "economicspace", "zone", or "customsunion" score high on this topic. We can also differentiate the EU FTA and the CU topic from other trade topics which might be discussed in UBW, but which are not directly related to the EU FTA and the CU.[19]

Figure (3) below shows smoothened trends for the EU FTA and the RU CU topics over time, including 95% confidence intervals.[20] The smoothened time trend shows both the increasing prevalence of the EU FTA , and the simultaneous decline of the CU salience over time. It also highlights the short but sharp decline in EU FTA prevalence in 2013, when the Ukrainian president Yanukovich declined to sign the EU FTA. After the overthrowing of his government, the EU FTA becomes more salient again. The latent topics estimated from the UBW articles are therefore good representations of the long-run policy process and the relative probabilities of the two trade policy options. Inspection of the words associated with topics, the documents associated with the topics, and the long-run trend resembling real-world events provide validity to our TPU measure.[21] In Appendix

[17]A well known application in Political Science are party manifestos, which contain information about the election year, the type of election (federal, subnational), and the author (the party). See Volkens et al. (2015).

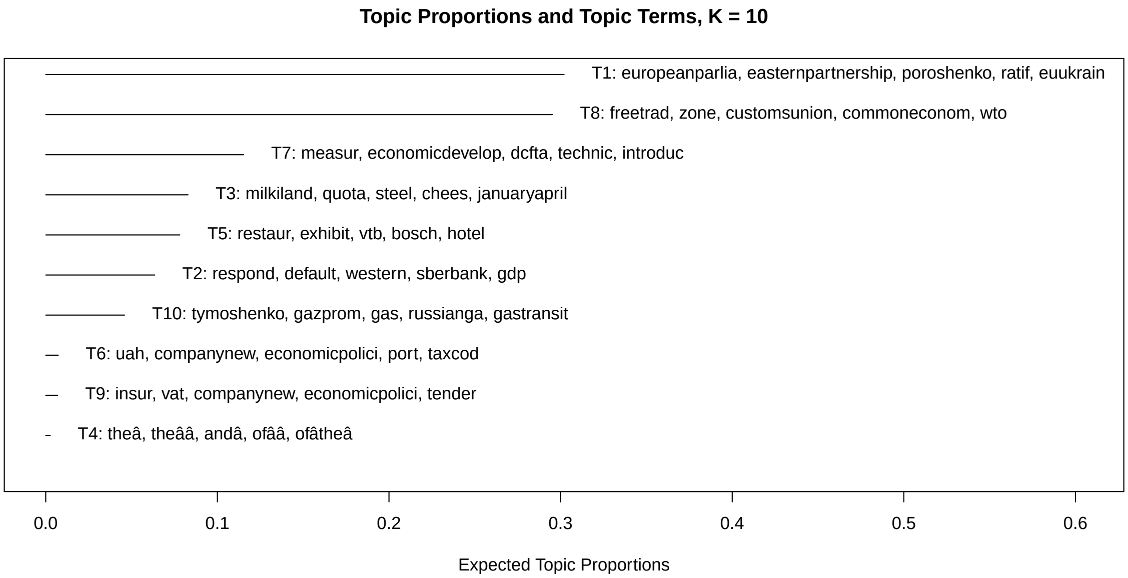
[18]Here, we report the so-called "FREX" terms. These are words associated with the topic which appear with high probability *and* exclusively identify only this topic, but not other topics.

[19]For instance, topic 3 is about steel and cheese quotas ("quota, "pipe", "dairy",...) and topic 10 is about Russian gas imports ("gazprom", "russiangas", "gastransit",...), two topics which are also very contentious in Ukrainian trade relations. In Appendix A5, we also provide snippets of articles that score high on our two topics of interest.

[20]A graph showing the the raw *weekly* and *monthly* prevalence of topics is presented Appendix A5. See figure (A5).

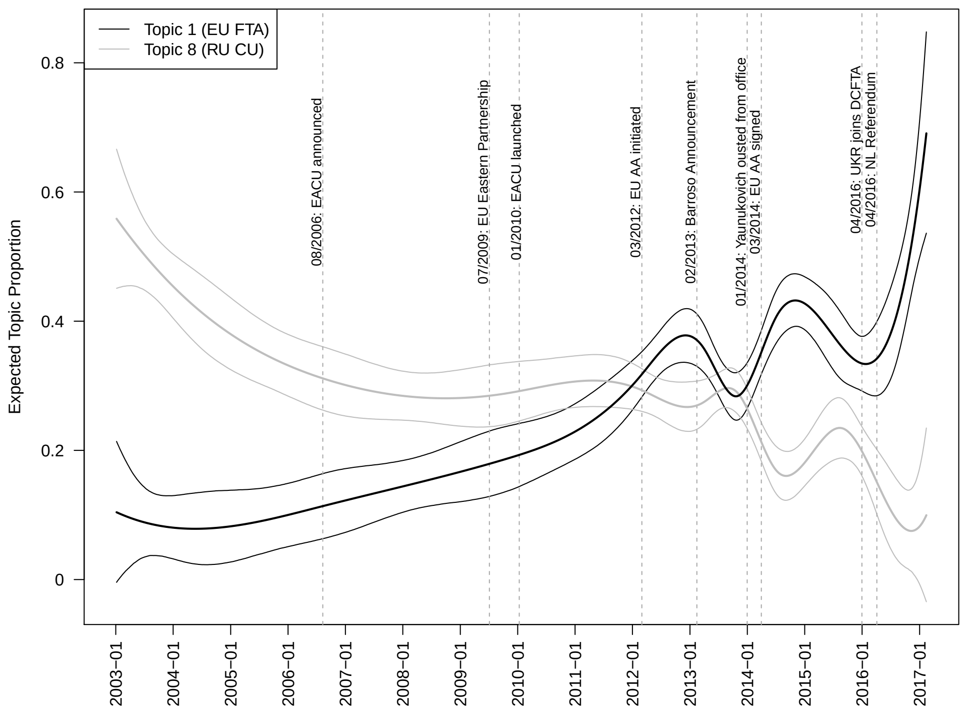
[21]In Appendix A4, we provide tests of non-stationarity of our measure, and reject it for both time-series.

Figure 2: Mean Topic Proportions across $K = 10$ topics, estimated using the Structural Topic Model



A4, we provide evidence that our measure is not driven by changes in tone, or *how* UBW reports about the FTA and the CU.

Figure 3: Smoothened Time trend for the EU FTA and the RU CU topic, 2003-2017. The expected Topic Proportions from the STM described above as spline of time. 95% confidence intervals are shown.



FDI and TPU

We start presenting our empirical results of the effects of TPU on firm's performance with the analysis of FDI. We look at quarterly data from 2003:Q1 until 2013:Q4. Our sample consists of all manufacturing firms in Ukraine that had a positive FDI stock in that time period. The dependent variable is the natural log of FDI stock from country j at time t, invested in company i. We estimate the following model

$$\ln FDI_{ijt} = \alpha_0 + \alpha_1 p_{EU,t} \times EU_t + \alpha_2 p_{EU,t} \times CU_t + \alpha_3 p_{CU,t} \times EU_t + \alpha_4 p_{CU,t} \times CU_t + \alpha_5 p_{EU,t} + \alpha_6 p_{CU,t} + \alpha_7 EU_t + \alpha_8 CU_t + D_Q + D_I + D_R + D_t + D_{ij} + \varepsilon_{it} \quad (10)$$

where p_{EU} is the likelihood of Ukraine signing an FTA with the EU and p_{CU} is the likelihood of Ukraine joining the CU with Russia. We proxy these probabilities by the relevant topics proportions, described in the previous section. To arrive at the quarterly measures, we use simple averages of the monthly measures shown in Figure A4. EU is an indicator variable for FDI sourced from the EU countries, *CU* is an indicator variable for FDI sourced from the CU countries; the D's represent a set of quarter (Q), industry (*I*), region (*R*), time (t), and firm-source country (*ij*) fixed effects. Standard errors are clustered at the firm-level.

Our variables of interest are the interactions of the EU and CU dummies with the probability of EU FTA and CU. According to the model, developed in Section 3, TPU reduction encourages more exports which require additional investments and incur sunk costs at the firm level. For vertical FDI, driven by the globalization of supply chains and outsourcing, that would encourage more FDI form countries which experience increased likelihood of liberalizing trade with Ukraine. Therefore, we expect coefficients α_1 and α_4 in equation (10) to be positive, because increased expectations about signing FTA and CU would encourage FDI sourced from EU and CU countries respectively. On the other hand, we expect α_2 and α_3 to be negative, because higher chances to sign the FTA with EU would reduce FDI sourced from CU and vice versa. Also, the relationship between TPU and FDI should be weaker for FDI from CU countries, since the EU FTA does not mean a change in Ukrainian trade policy vis-a-vis the CU, while joining the CU implies substantive changes vis-a-vis EU countries.

The results are presented in Table 2 below. According to our estimates, FDI from the EU is highly sensitive to changes in TPU at the level of firm-source country even when controlling for time, industry, and region characteristics. For a sample of all manufacturing firms, a standard deviation increase in the probability of signing the EU FTA increases FDI within firm-source country by 4 percent if we use the contemporaneous values of the EU FTA probabilities (columns 1-5) and by 5.3 percent if we use the lagged values of EU FTA probabilities (columns 7, 8). For a sub-sample of large firms (column 6), the effect is 6 percent increase in FDI. Likewise, a standard deviation increase in probability of Ukraine joining CU reduces FDI from EU within the range of 1.5 to 2.5 percent. These changes are substantive, given that none of the two mutually exclusive policies is enacted yet within the time frame of investigation. Finally, based on the most conservative estimates in column (5), joining the EU FTA would boost FDI from EU by 34 percent.

Table 2: FDI and trade policy uncertainty

	Base	+empl	+Ind	+Reg	Time	Big	Lag	Lag+time
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
EU=1 × p_{EU}	.396**	.378**	.380**	.374**	.345**	.535**	.468**	.453**
	(.105)	(.111)	(.110)	(.110)	(.112)	(.134)	(.131)	(.132)
CU=1 × p_{EU}	-.256	-.354*	-.354*	-.354*	.004	-.189	-.166	.145
	(.157)	(.164)	(.163)	(.163)	(.171)	(.368)	(.205)	(.222)
EU=1 × p_{CU}	-.150**	-.143**	-.146**	-.142**	-.132**	-.102*	-.153**	-.136**
	(.050)	(.051)	(.051)	(.051)	(.051)	(.048)	(.047)	(.046)
CU=1 × p_{CU}	.275	.311*	.307*	.303*	-.011	.272	-.055	-.216
	(.144)	(.145)	(.144)	(.144)	(.152)	(.370)	(.231)	(.237)
p_{EU}	.346**	.523**	.526**	.526**	2.660**	2.892**	.478**	2.022**
	(.087)	(.093)	(.092)	(.092)	(.197)	(.268)	(.112)	(.184)
p_{CU}	-.221**	-.276**	-.273**	-.272**	.000	.000	-.293**	.000
	(.040)	(.042)	(.041)	(.041)	(.)	(.)	(.037)	(.)
EU=1	.176**	.205**	.206**	.205**	.044	.012	.158**	.039
	(.039)	(.040)	(.040)	(.040)	(.043)	(.042)	(.039)	(.043)
CU=1	.037	.100	.100	.099	-.070	-.115	.121	-.037
	(.062)	(.065)	(.064)	(.064)	(.067)	(.114)	(.088)	(.090)
ln($empl$)		.099**	.100**	.101**	.121**	.133**	.101**	.121**
		(.012)	(.012)	(.012)	(.012)	(.014)	(.012)	(.012)
Quarter	Yes	Yes	Yes	Yes	No	No	Yes	No
Industry	No	No	Yes	Yes	Yes	Yes	No	Yes
Region	No	No	No	Yes	Yes	Yes	No	Yes
Time	No	No	No	No	Yes	Yes	No	Yes
Observations	72689	68276	68276	68276	68276	56981	57851	57851
R^2	.968	.968	.968	.968	.970	.970	.969	.971

* p<0.05, ** p<0.01

Robust standard errors clustered at firm level are in parentheses. The dependent variable is the log of the value of the cumulative foreign direct investment in firm i from country j at quarter-year t. p_{EU} captures the likelihood of Ukraine signing the FTA with the EU. p_{CU} captures the likelihood of Ukraine joining the CU with Russia. All regressions include firm-source country fixed effects

The effect of TPU on FDI from CU is less robust and disappears once we include time fixed effects. We anticipate this result, because as we argued above, joining EU FTA does not automatically implies changes in trade policy of Ukraine with CU countries. Interestingly, the effect of the likelihood of signing EU FTA (p_{EU}) on FDI is positive, while the increase in likelihood of joining CU (p_{CU}) has a negative effect on FDI coming from any country. Also, EU countries invested significantly more in the Ukrainian firms relative to other countries, as indicated by a positive and significant coefficient of the EU indicator variable. We also confirm that larger firms receive more FDI, as indicated by a positive and significant coefficient of log of employment.[22]

Trade and TPU

We proceed with the estimation of the relationship between trade and TPU. We formulate an equation in the first differences and jointly evaluate how TPU regarding the EU and the CU influences export and import flows. We estimate the following equation

$$\begin{aligned} D.\ln Trade_{ijkt} \quad = \quad & d_0 + d_1 D.EU + d_2 D.p_{EU,t} + d_3 EU \times D.p_{EU,t} + d_4 EU_{jt} \times D.p_{CU,t} \\ & + d_5 D.CU_{jt} + d_6 D.p_{CU,t} + d_7 CU_{jt} \times D.p_{EU,t} + d_8 CU_{jt} \times D.p_{CU,t} \\ & + X_{it}\beta + D_Q + D_R + D_I + D_{ijk} + D_t + u_{ijt} \end{aligned} \tag{11}$$

where i is a firm, j is a country, k is a product, t is time (quarter-year), $D.X = X_t - X_{t-1}$is the difference operator. The dependent variable is the log of either export or import values. EU is an indicator variable for whether country j is an EU member or not, and p_{EU} is the likelihood of Ukraine signing a FTA with EU. CU is a dummy variable indicating whether country j is a CU member or not. p_{CU} is the likelihood of Ukraine joining CU. X is a set of additional controls, including firm size and its productivity. We also control for D's, which indicate a set of quarter, region, industry, time, and firm-destination-product fixed effects.

We estimate a number of models where we interact the CU and EU dummies with the probability of signing the EU FTA, p_{EU}, and the probability of joining the CU, p_{CU}, respectively. We expect an increase in the probability of joining the CU to increase exports to CU, and increase in the probability to sign the EU FTA to decrease exports to CU. Conversely, an increase in the CU probability decreases exports to EU countries and a higher probability to sign the EU FTA increases exports to the EU.

[22]We also controlled for productivity, by including TFP estimates, but found that once the firm size is accounted for, there is no additional effect of productivity on FDI.

Table 3: Trade and trade policy uncertainty.

	Export				Import			
	Base	+TFP	+MFN	+Ind&Reg	Base	+TFP	+MFN	+Ind&Reg
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
EU=1 $\times$ D.p^{EU}	.094	.084	.100	.100	.262**	.248**	.250**	.249**
	(.060)	(.060)	(.061)	(.061)	(.066)	(.066)	(.066)	(.066)
EU=1 $\times$ D.p^{CU}	-.087*	-.082*	-.096**	-.096**	-.099**	-.093**	-.093**	-.091*
	(.034)	(.035)	(.035)	(.035)	(.035)	(.036)	(.036)	(.036)
CU=1 $\times$ D.p^{EU}	.114	.099	.123	.121	-.073	-.066	-.064	-.060
	(.074)	(.074)	(.075)	(.075)	(.104)	(.105)	(.105)	(.105)
CU=1 $\times$ D.p^{CU}	-.375**	-.367**	-.378**	-.378**	-.010	-.019	-.019	-.010
	(.065)	(.065)	(.066)	(.066)	(.089)	(.089)	(.089)	(.090)
D.p^{EU}	5.097**	5.027**	4.815**	4.828**	6.217**	6.252**	6.244**	6.238**
	(.439)	(.442)	(.449)	(.449)	(.440)	(.442)	(.442)	(.443)
D.p^{CU}	3.519**	3.488**	3.409**	3.417**	4.916**	4.958**	4.956**	4.954**
	(.196)	(.198)	(.201)	(.201)	(.193)	(.194)	(.194)	(.195)
D.EU	.041	.039	.032	.032	.055	.046	.046	.046
	(.040)	(.040)	(.041)	(.041)	(.036)	(.037)	(.037)	(.037)
D.CU	.006	-.007	.001	.001	.067	.070	.069	.067
	(.029)	(.029)	(.029)	(.029)	(.041)	(.041)	(.041)	(.041)
D.ln($empl$)	.110**	.125**	.128**	.127**	.216**	.233**	.233**	.234**
	(.016)	(.017)	(.017)	(.017)	(.015)	(.017)	(.017)	(.017)
D.TFP		.125**	.126**	.125**		.073**	.074**	.075**
		(.013)	(.013)	(.013)		(.010)	(.010)	(.010)
D.ln$(1+\tau_{MFN})$			-.273	-.271			-.220	-.217
			(.198)	(.198)			(.619)	(.619)
Time	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry	No	No	No	Yes	No	No	No	Yes
Region	No	No	No	Yes	No	No	No	Yes
Observations	357459	352198	340866	340866	641054	627579	627315	627315
R^2	.176	.175	.173	.173	.194	.193	.193	.193

* p<0.05, ** p<0.01

Robust standard errors are in parentheses. The dependent variable is the first difference in log of the value of HS 4 digit product k export/import of firm i to/from an EU country j within quarter-year t. p^{EU} captures the likelihood of Ukraine signing the EU FTA. EU is an indicator variable that takes the value of 1 if country j is EU member and 0 if otherwise. p^{CU} captures the likelihood of Ukraine joining the CU with Russia. CU is an indicator variable that takes the value of 1 if country j is a CU member and 0 if otherwise. The operator D indicates first differences of a variable. All models are estimated with firm-country-product fixed effects.

The results from estimating equation (11) are shown in Table 3. Columns (1)-(4) report results for exports from Ukraine. As predicted by our model, we find that uncertainty plays a significant role in explaining export of Ukrainian firms to EU as shown by a negative and significant coefficient of the variable $EU \times D.p_{CU}$. This finding is consistent with our theoretical model under assumption that the CU policy state worsens access of the Ukrainian firms to the EU, as may be the case as a result of the WTO disputes and non-tariff measures. The export to CU, on the other hand, does not responds negatively and significantly to higher chances of signing the EU FTA, because the FTA does not automatically imply more difficult access to the CU markets.

Columns (5)-(8) report results for imports to Ukraine. Higher chances of joining CU significantly reduces imports from the EU, as indicated by the coefficient of the cross term $EU \times D.p_{CU}$. Moreover, EU-imports positively and significantly respond to higher chances of signing EU FTA, as indicated by the coefficient of $EU \times D.p_{EU}$. There is no significant effect of uncertainty on imports from CU, which is consistent with our model because joining EU does not automatically changes tariffs applied to imports from CU countries. This highlights again our expectation that firms from EU member states should expect to be more negatively affected by the CU than CU members by the EU agreement, and is thus consistent with our theoretical model.

TPU and level of tariff protection

Finally, our theoretical model predicts that products which are protected by higher MFN tariffs should benefit more from the reduction in trade policy uncertainty than those with lower MFN tariffs. This prediction allows us to add variation across products and identify the TPU effects using both variation *across time and products*. We test this prediction by interacting our TPU measures with product-specific MFN tariffs. Here, we focus on interaction terms: $p_{EU} \times \ln(1+\tau_{MFN}^{EU})$ for exports of Ukrainian firms to EU member states and $p_{EU} \times \ln(1+\tau_{MFN}^{UKR})$ and $p_{CU} \times \ln[(1+\tau_{MFN}^{CU})-(1+\tau_{MFN}^{UKR})]$ for imports of Ukrainian manufacturers from the EU.[23] We expect positive coefficients for the first two cross terms and the negative coefficient for the last cross term. Products with higher tariff protection should expand more if the likelihood of signing the EU-Ukrainian FTA increases, resulting in an increased probability of tariff rates being reduced to zero. However, if the likelihood of joining CU with Russia increases, it increases expectations that Ukraine switches from its own tariff schedule to the schedule of the customs union, which would result in lower imports from EU countries for products with higher CU protection relative to Ukrainian tariffs. Table 4 shows the results from this final test for Ukrainian exports to the EU (columns 1-5) and Ukrainian imports from EU (columns 6-10).

[23] The export equation has only one interaction term because joining the customs union does not change tariffs faced by Ukrainian exporters that export to EU or CU countries.

Table 4: Trade with EU, tariff protection, and trade policy uncertainty

	Export					Import				
	Base	TFP	Empl	IndReg	Trend	Base	TFP	Empl	IndReg	Trend
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$p^{EU} \times \ln(1+\tau_{MFN})$	.546	.664	1.37	1.46	1.12					
	(1.33)	(1.310)	(1.26)	(1.27)	(1.26)					
$\ln(1+\tau_{MFN})$	.488	.257	.019	-.061	2.35					
	(2.21)	(2.19)	(2.20)	(2.19)	(2.24)					
$p^{EU} \times \ln(1+\tau_{UKR})$						2.111*	1.96*	2.41**	2.45**	2.36**
						(.88)	(.87)	(.85)	(.85)	(.83)
$p^{CU} \times \ln((1+\tau_{CU})/$ $(1+\tau_{UKR}))$						-1.205**	-1.19**	-1.65**	-1.62**	-1.04**
						(.37)	(.38)	(.36)	(.36)	(.34)
$\ln(1+\tau_{UKR})$						-1.79**	-1.36**	-1.59**	-1.59**	.025
						(.42)	(.42)	(.41)	(.41)	(.38)
p^{EU}	-.044	-.135	-.074	-.095	-.485**	.097	.012	.015	.002	-.305**
	(.106)	(.084)	(.073)	(.074)	(.072)	(.070)	(.072)	(.071)	(.071)	(.049)
p^{CU}	-.175**	-.137**	-.217**	-.205**	.230**	.080	.146**	.143**	.151**	.368**
	(.047)	(.045)	(.044)	(.044)	(.037)	(.047)	(.048)	(.048)	(.048)	(.039)
TFP		.140**	.141**	.194**	.161**		.146**	.133**	.173**	.143**
		(.022)	(.018)	(.021)	(.019)		(.020)	(.020)	(.022)	(.023)
$\ln(empl)$			.376**	.384**	.415**			.415**	.424**	.429**
			(.025)	(.025)	(.026)			(.030)	(.030)	(.030)
Quarter	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry	No	No	No	Yes	Yes	No	No	No	Yes	Yes
Region	No	No	No	Yes	Yes	No	No	No	Yes	Yes
Trend	No	No	No	No	Yes	No	No	No	No	Yes
Observations	182045	176876	176876	176876	176876	905096	881116	881116	881116	881116
R^2	.866	.866	.868	.868	.869	.811	.810	.812	.812	.812

* p<0.05, ** p<0.01

Robust standard errors clustered by firms are in parentheses. The dependent variable is the log of the value of HS 4 digit product k export/import of firm i to/from an EU country j within quarter-year t. The cross term $p^{EU} \times \ln(1+\tau_{MFN})$ captures effect of trade policy uncertainty on exports of goods with different levels of tariff protection. The cross term $p^{EU} \times \ln(1+\tau_{UKR})$ captures the effect of the likelihood of the EU FTA on imports of goods with different levels of tariff protection. The cross term $p^{CU} \times \ln((1+\tau_{CU})/(1+\tau_{UKR}))$ captures the effect of the likelihood of joining the RU CU on imports of goods with different levels of tariff protection. p^{EU} captures likelihood of Ukraine signing the EU FTA. p^{CU} capture the likelihood of Ukraine joining the CU with Russia. All models are estimated with firm-country-product fixed effects.

For Ukrainian exports we do not find that the cross-term has a significant effect. An increase in the probability of signing the EU FTA does not seem to increase exports for products with higher protection, because the cross-term coefficient is not significant, albeit positive as we expect. However, for imports we observe a strong positive effect for the coefficient of $p_{EU} \times \ln(1+\tau_{MFN}^{UKR})$, indicating that imports of products with high levels of tariff protection in Ukraine expand more when the likelihood of the FTA with the EU is high. The coefficient on the probability of joining the CU with Russia is also correctly signed in the model for imports, albeit not always significant. When the likelihood of Ukraine joining the CU is high, we find a negative effect imports from the EU. The controls employed have the expected signs for both imports from and exports to the EU. In line with the heterogeneous firms literature, more productive and large firms export and import more. Our results are robust to inclusion of industry and regional dummies (columns 4 and 9) and to accounting for time trend (columns 5 and 10). The magnitude of the effect is also large. Based on the column (6) estimates, by signing EU FTA and removing TPU would increase imports from EU by 13.4 percent. The effect of lower tariffs on the other hand would increase imports by 5.3 percent. To the extent that imported manufacturing inputs are used to increase productivity, this hints at potential productivity-reducing effects of high TPU. For exports, the effect is smaller. Elimination of TPU with EU would increase exports to EU by 4.8 percent.

5 Conclusion

This paper highlights the importance of trade policy uncertainty for firm-level imports of intermediates and investment, using the case of Ukraine. Our paper provides three main contributions. First, we extend a heterogeneous firm model with monopolistic competition by adding the choice to import intermediate inputs, which can be sourced from foreign or domestic suppliers. Second, we test empirically the effect of TPU on imports of intermediate inputs and on firm-level Foreign Direct Investment. We find that a reduction in TPU has both a strong and positive effect on FDI and import of intermediate inputs. Full reduction of TPU amounts to an increase in FDI from EU countries of about 34 percent, and would increase imports of intermediate goods by 13.3 percent. We also find that products with higher MFN tariffs expand more strongly as TPU is reduced which is consistent with our model. Given the importance of intermediate inputs for firm-level productivity, reducing TPU could be particularly beneficial for firms in developing countries.

Finally, we provide a new measure of TPU by using machine learning techniques to analyze a large collection of over 2000 press news releases on Ukrainian economic policy in order to approximate uncertainty between the EU FTA and the RU CU. The measure directly reflects political swings in Ukraine, and thus describes political dynamics which would have been overlooked by existing measures like differences in tariff schedules. Similar techniques can be used to investigate the effects of TPU when other measures are unavailable. First, such a measure can be used for policies other than tariff changes that might induce trade policy uncertainty. Examples of these include the joining of military alliances, or joining international organizations that exclude the membership in others. The measure can also be used when barriers to trade are not publicly available, like for many developing and least developed countries.

There are several possible extensions of this paper. We want to extend to data through 2016 and concentrate on the period 2013-2016 in order to analyze the impact of the annexation of Crimea and the resulting war in Eastern Ukraine on firm-level trade and investment. We also want to analyze regional newspapers in order to get regional variation in our TPU measure. Moreover, outside of the Ukrainian case, a number of contemporaneous political events provide fertile ground for testing the effect of trade policy uncertainty on trade and investment patterns. The time between the recent Brexit referendum and the announcement of the type of relationship between Great Britain and the EU could be analyzed as a source of uncertainty for firms. More generally, given the current backlash against free trade, with the UK leaving the EU and the and decision of the US not to ratify the Transpacific Partnership, we see particular relevance in quantifying the effects of trade policy uncertainty on firm-level trade and investment.

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6 Appendix (For Online Publication)

A1 Exporting under uncertainty

If the future is uncertain, with the source of uncertainty generated by the state of the trade policy, the firm has two decisions to make. First, it decides on whether to export or not. We assume that the firm is risk neutral, so it cares only about expected value. [24] We also assume that the transition probability matrix (3) is a common knowledge, shared by all firms. Second, the firm decides on the optimal timing to start exporting.If it starts exporting today, its expected present value of profits is given by

$$\Pi_e(a_s,c) = \pi(a_s,c) + E_s \sum_{t=1}^{\infty} \beta^t \pi(a_s^{'},c) \tag{12}$$

Alternatively, it may delay the decision, solving the following stopping problem

$$\Pi(a_s,c) = \max\left\{\Pi_e - I_{EX}, \beta E_s \Pi(a_s^{\prime},c)\right\} \tag{13}$$

where the first element in brackets is the expected benefits of investing today and the second element is the expected benefit of delaying the decision for one period. The value of the option of investing into exporting is given by

$$V_s \equiv \Pi(a_s,c) - \Pi_e(a_{s,}c) + I_{EX} \tag{14}$$

and the optimal stopping problem can be re-formulated as

$$V_s = max\{0, \beta E_s V_{s'} - \pi(a_s,c) + I_{EX}(1-\beta)\} \tag{15}$$

where exporting decision is taken when $V_s = 0$.

Consider a firm evaluating the decision to start exporting to the EU. Observing (15) and given assumptions about the TPU process, the option value V_s is decreasing with $\pi(a_s,c)$, therefore decreasing in a and increasing in c. When a increases (trade policy switches from MFN to FTA state), the probability that it will stay in the FTA state goes up (in fact we assume that it is 1), while probability that a takes lower values (switches to MFN or CU) diminishes, in other word Λ_{FTA} stochastically dominates Λ_{MFN}, which in turn stochastically dominates Λ_{CU}. This leads to $E_s V_{s'} = \int V_{s'} d\Phi(a_{s'}|a_s)$ is increasing in c. According to Dixit and Pindyck (1994), this leads to a

[24] It might be an interesting extension to consider a risk averse firm, which imposes different modifications of the objective function, and the firm faces a trade off of lower expected return in order to reduce the risk of an adverse outcome.

Table A1: Differences in applied MFN tariffs between Ukraine and CU in 2003-2013

Tariff Year	Mean			Number of lines with	
	Ukraine MFN tariff τ_{UKR}	CU MFN tariff τ_{CU}	Difference $\tau_{CU} - \tau_{UKR}$	higher tariffs $\tau_{UKR} > \tau_{CU}$	lower tariffs $\tau_{UKR} \leq \tau_{CU}$
2003	6.94	11.92	4.93	196	949
2004	6.34	11.61	5.14	158	987
2005	5.75	11.34	5.50	130	1015
2006	5.17	10.78	5.55	164	1036
2007	5.13	10.58	5.38	175	1029
2008	5.18	10.53	5.32	179	1028
2009	4.70	10.66	5.94	151	1057
2010	4.81	9.70	4.89	185	1028
2011	4.67	9.86	5.20	187	1032
2012	4.67	11.18	6.50	92	1129
2013	4.77	10.12	5.35	128	1093
All	5.29	10.78	5.43	159	1035

unique cutoff c_s^U such that all firms with $c \leq c_s^U$ export to EU and firms with $c > c_s^U$ do not export to EU. Moreover, given our Markov process the cutoff is given by

$$c_{EX,MFN}^{U,EU} = \left(\frac{1 - \beta(1 - p_{CU})}{1 - \beta(1 - \frac{a_{CU}}{a_{MFN}} p_{CU})} \right)^{\frac{1}{1-\sigma}} \times c_{EX,MFN}^{D,EU} \tag{16}$$

A2 Dynamics of tariffs in Ukraine and customs union in 2003-2013

Table A1 presents the evolution of the applied MFN rates of Ukraine and CU between 2003-2013, average difference in those rates, number of lines at HS4 digit level where the Ukrainian MFN rates are higher then the CU rates, and the number of lines where the Ukrainian MFN rates are lower.

A3 Building our Collection of Texts

We first downloaded all news briefs from Nexis that are somehow related to either the EU FTA or the Russian CU using Boolean search terms.[25] Figure A1 below shows a typical article from Ukraine Business Weekly, downloaded from Nexis in .txt format. We split the articles using the

[25] The following Boolean search term was used: "HLEAD(russian federation OR russia* OR eu OR european union*) AND HLEAD(ukrain*) AND Body(trade agreement* OR free trade OR customs union OR trade deal OR free trade agreement OR eurasian customs union OR eacu OR eurasian economic union OR eeu OR association agreement OR dcfta OR aa)"

“### of ### Documents” line and retrieved the publication date using regular expressions. We also extracted the title for each article, and then retained only the text body of each article for further processing. All meta-data was removed prior to applying the topic models. We find 2201 articles between 2003 and 2016, amounting to about 15 articles per month on average.[26] Duplicate articles and non-business news where excluded from the search. Figure (A2) shows the total number of UBW articles per month retrieved from Nexis and provides a description of the raw data.

The raw articles contain boiler plates and meta information, such as copyright information, title, length, and the date of publication. Figure (A1) shows a typical article downloaded, and the additional information provided in the *.txt* files. From the raw article collection, we retrieved title and publication date. We then erased all the meta information using *regular expressions* until we are left with only the text body of the articles. Most quantitative text analysis techniques like the models we are using make the *bag-of-words* assumption, ignoring the order of words in a document. The only textual property that matters for the analysis of the texts is the relative frequency with which words occur within a given document in our collection of texts. However, we treat bigrams like “vladimir putin” and compound terms like “customs union” as single terms in the analysis, as they convey meaning in conjunction.

Finally, we remove common English stopwords that do not convey meaning. We also stem the endings of words, leaving only the word “roots” for further analysis and remove words occurring in less than one or two documents.[27] After these preparatory steps, the articles are translated into a “document-term” matrix (dtm) which can be further analyzed. The *dtm* is a matrix of the form $d \times w$, where rows d represent single documents (here individual news releases) and the columns w represent terms and how frequently they occur in each document, resulting matrix in a large and sparse 2201×5968 matrix which can be further analyzed.

Figure A2 below shows the number of articles per month downloaded from Nexis. One can clearly see the overall increase in discussion of any sort of trade agreement, with either Russia or the European Union over time, peaking in 2014 around the final conclusion of the EU FTA and the peak of the trade tensions between the EU and Russia. There are also two low points in the number of articles, one at the end of 2006, and another around the beginning of 2011. These represent structural breaks in the textual data available in Nexis. During these time frames only a limited number of articles is available online. In 2006, all single articles are joined in one document for one month.In 2011, there is one month without any recordings from Ukraine Business weekly. However, this does not affect our TPU measure. For discussion of the time periods with missing

[26] Including more terms did only increase the number of documents marginally and hence, we are confident that the sample of news releases is not biased in either on or the other direction.

[27] All of the steps in this paragraph are standard in quantitative text analysis. For a good review and explanation of “stopwords”, “stemming”, and “bigrams” and pre-processing of documents see Grimmer and Stewart (2013).

Figure A1: Example Ukraine Business Weekly article in raw format, as retrieved from Nexis

1 of 219 DOCUMENTS

Ukraine Business Weekly

December 26, 2012

ECONOMIC POLICY

LENGTH: 215 words

DATELINE: Kyiv December 20

BROK: EU-UKRAINE ASSOCIATION AGREEMENT SHOULD BE SIGNED IN NOVEMBER 2013

The EU-Ukraine Association Agreement should be signed in November 2013 at a summit in Vilnius, Chairman of the European Parliament's Foreign Affairs Committee Elmar Brok has said.

"The association agreement, including a free trade agreement, should be signed at a summit in Vilnius in November 2013," he said at a press conference in Kyiv on Thursday.

Brok recalled that in order to sign the agreement, Ukraine must fulfill the conditions outlined in European Parliament resolution, in particular, hold elections in line with European standards, create an Electoral Code, taking into account the opinion of the Venice Commission, reform the law enforcement system, and reduce the powers of the Higher Council of Justice.

He also stressed the need to remove selective justice. He said that it was necessary to resolve issues on the cases of former Prime Minister Yulia Tymoshenko and former Interior Minister Yuriy Lutsenko.

"The cases of Tymoshenko and Lutsenko should be resolved from the very beginning. If they are resolved, it will be much easier to fight for the European prospects of Ukraine," he said.

Brok noted that Germany's proposal on Tymoshenko's treatment in Charité Clinic (Germany) "still remains in force."

LOAD-DATE: January 9, 2013

LANGUAGE: ENGLISH

DOCUMENT-TYPE: Emerging Markets

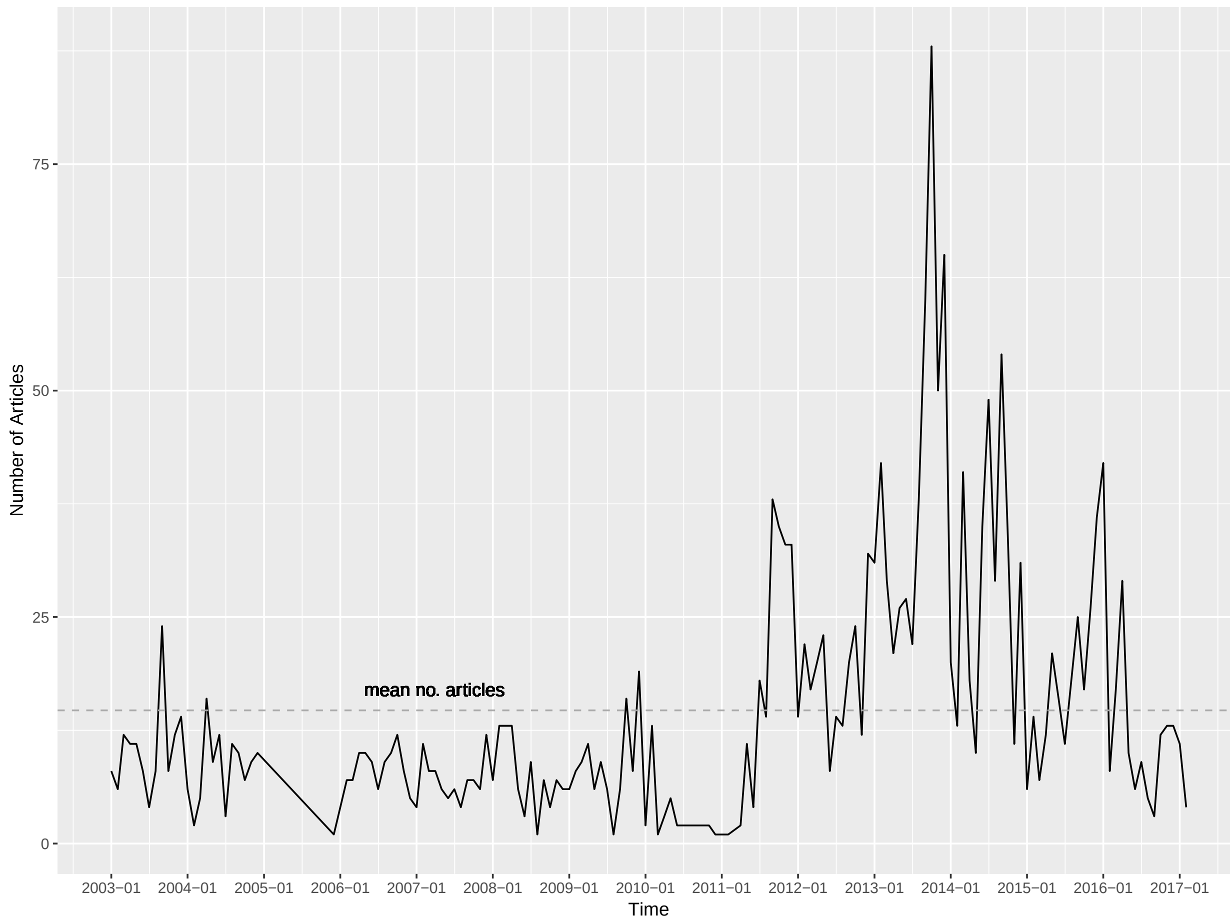
PUBLICATION-TYPE: Newsletter

articles, see our discussion of our TPU measure in the main text.

Many single words in the UBW press releases naturally occur together forming so-called bigrams, like "vladimir putin" or compound terms like "customs union". We do not want to treat these as individual words, as they clearly appear and convey meaning together. Table (**??**) below shows the most commonly occurring bigrams, ranked by *G2* (a log-likelihood statistic.). Some of the most commonly occurring bigrams are "association agreement" or "free trade". These are further cleaned by removing bigrams with stopwords[28] which leaves about 360 bigrams. In the articles, these are replaced concatenated with a "_", so that they can be treated as an single term in the application of the topic model.

[28] Stopwords are terms which do not convey meaning, like "the", "also", or "have".

Figure A2: Number of articles retrieved from Nexis over time



A4 The Text Analysis Model and Diagnostics

For measuring TPU from the documents, we use so-called "topic models", developed by computer scientists for the analysis and organization of large-scale text corpora. Topic models analyze relative word occurrences in un-labeled documents in order to discover "themes" that run through the documents.[29] Topic models belong to the family of unsupervised classification methods because they infer the content of topics from the texts rather than assuming them. It is therefore crucial to understand that topics *are not defined ex ante* by the researcher, like in hand-coding of documents based on pre-defined dictionaries.[30]

The simplest topic model is the *Latent Dirichlet Allocation* (LDA)[31], a generative probabilistic model for discrete data (Blei et al., 2003). Topics are defined here as a distribution over a vocabulary of words which represent interpretable themes. The LDA is a mixed membership Bayesian model, in which documents are represented as a mixture of topics. Thus, each document can be conceived as a vector of proportions, indicating the fraction of words belonging to a latent topic. Generative probabilistic models treat documents as if they had been generated according to a particular process involving observed and latent variables. The joint probability distribution of that process can be used in order to compute the conditional distribution, i.e. the the posterior distribution, of the hidden variables, given the observed variables. The observed variables are the document-level words, and the unobserved variables refer to the topic structure.

A topic K is defined as a distribution over a fixed vocabulary V. The data generating process is as follows: the LDA assumes that documents (press releases) are created by K topics. Across documents, we first randomly choose a distribution over topics β_k. Each document is modeled as a distribution over K topics, θ_d. Within each document, words are generated by a two step process. First, for each word $z_{d,n}$, one draws a topic for that word from a multinomial distribution $z_{d,n} \sim Mult(\theta_d)$ (with $z_{d,n}$ indexing the topic assignment for the n-th word in document d). Second, an actual word $w_{d,n}$ is drawn from a distribution over the vocabulary $w_{d,n} \sim Mult(\beta_{z_{d,n}})$ where $\beta_{k,v}$ is the probability of drawing the v-th word in the vocabulary for topic k. The likelihood of a word for a given topic is then the probability of a topic within a given document times the probability of a term in the overall word distribution, $p(z_{d,n}) \cdot p(w_{d,n})$. This joint distribution of the latent and observed parameters (Blei et al., 2012) is formally given by

[29] These models have been successfully applied in both Political Science (Grimmer, 2010; Roberts et al., 2014) and Economics (Mueller and Rauh, 2016), and many more fields such as Genetics or Information Science (Blei, 2012).

[30] For a good description of the basics of dictionary-based text analysis see Neuendorf (2002, CH6). A well-known application of dictionary-based methods keywords representing left-right ideology in order to estimate scores of party positions using their election manifestos (Laver and Garry, 2000).

[31] Note that this section provides only a short and non-technical introduction into topic models, oriented at Roberts et al. (2014). The interested reader is referred to Blei et al. (2003) for the LDA topic model, and to Roberts and Stewart (2015) for more technical details on the Structural Topic Model (STM).

$$p(\beta_{1:K}, \theta_{1:D}, z_{1:D}, w_{1:D}) = \prod_{i=1}^{K} p(\beta_i) \prod_{d=1}^{D} p(\theta_d) \left(\prod_{n=1}^{N} p(z_{d,n}|\theta_d) p(w_{d,n}|\beta_{1:K}, z_{d,n}) \right).$$

Finally, the LDA assumes a Dirichlet prior for the topic proportions over documents d, so that $\theta_d \sim Dirichlet(\alpha)$ (Blei et al., 2003). This joint probability distribution of words documents and topics over a vocabulary can be used in order to calculate the probability of topics for each word, and the topic posterior probabilities θ_d for each document. Higher posterior likelihoods of a topic means that a high proportion of terms in document is related to that topic. The intuition behind LDA is that *documents* in a collection of documents (also called text *corpus*) contain multiple *topics* or themes. All documents in the collection are composed of the same topics, but they exhibit these topics in different proportions, and each word contributes to individual topics to a certain degree. Bigrams like “Association Agreement” or “Eastern Partnership” are related to the topic “EU-Ukraine FTA” , while terms like “customs union” or “EACU” would be related to the topic “Russia-Ukraine Customs Union”. Topic models do not require any prior information about the texts. Only the number of topics K needs to be determined ex ante by the researcher.

Structural topic models (STMs) allow the introduction of document-level covariates (e.g. date, publication type, outlet, author) similar to covariates in regression models, in order to increase model fit and allow for topics to vary by covariates (Roberts et al., 2014).[32] The document-level covariates can affect either topical prevalence, topical content, or both. *Topical prevalence* is the frequency with which a topic is discussed and *topical content* the variation in words used to discuss a topic (Roberts et al., 2014, p.4).[33] We make use of the weekly publication date of UBW articles in order to provide better estimates of topical prevalence over time. We concentrate on topical prevalence because we are interested in the change in salience of trade policies over time rather than the change in words used to describe them.[34]

We use the STM algorithm with $K = 10$ topics[35], and include the publication week as a flexible b-spline in order to adjust topic estimation for variation over time. Adjusting for general trends over time is key in order to retrieve relative changes in topic salience and correct for seasonality and absolute growth of the topics over time. The resulting topical prevalences for an EU FTA and a CU with Russia are described in the following section.

Most of the quantitative text analysis has been conducted in R using the *Quanteda* package

[32] A well known application in Political Science are party manifestos, which contain information about the election year, the type of election (federal, subnational), and the author (the party). See Volkens et al. (2015).

[33] Moreover, in STMS, topics can be correlated with each other and both the prior distribution over topics and the word use within topics can vary by covariates.

[34] See Appendix 3 for discussion and analysis of difference in tone or evaluative word use over time.

[35] We use a combination of automated methods and qualitative judgment in order to arrive at the number of topics. See Appendix 2 for a throrough discussion of of how we chose K.

(Benoit and Nulty, 2017) and the *STM* package (Roberts et al., 2014). In order to determine the number of topics, we use a combination of automated cross-validation methods and qualitative judgment of the semantic content of the topics. This is a standard procedure recommended both for simple LDA topic models (Blei et al., 2012) and structural topic models Roberts et al. (2014, p.1068-1070). First, we estimate the model for many different values of K, between 5 and 150 topics. The *searchK*-function in the *stm package (Roberts et al., 2015)* includes a few tests for choosing among these different numbers of topics (Wallach et al., 2009). Figure (A3) in the appendix plots the results of these analyses. The most important indicator here is the held-out log-likelihood, a cross-validation measure, and the model residuals, both in the upper panel of the figure. The held-out likelihood is the probability of words appearing within a document when these words have been removed. This measure is similar to cross-validation, when some proportion of the data is held out for estimation and then used for validation later on. In this case, we set the share of held-out words to 0.5. As one can see from the figure, the held-out likelihood gets larger (the predictive performance of the model increases) with more topics, indicating a better model fit as the model becomes more flexible. Similarly, the model residuals are reduced with a higher number of topics. Note also that the model fit in terms of the held-out likelihood does not improve anymore for $K > 50$. In fact, residuals get larger for more than 50 topics, and the model fit gets worse, too. This illustrates the bias-variance trade-off, and that we are over-fitting the model with $K > 50$ Lantz (2015). Hence, this first test shows that we need a number of topics smaller or equal to 50.

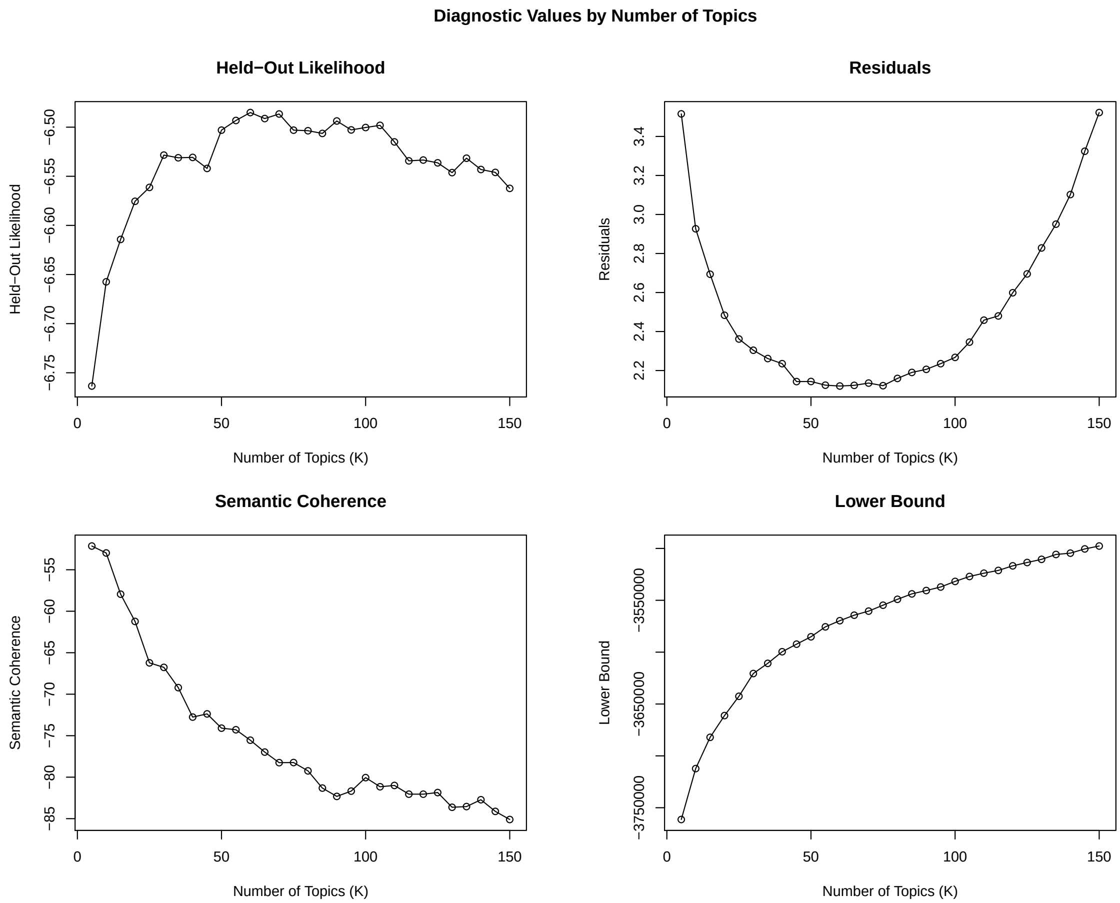
Second, we inspect the topics for different K and check whether they capture the CU with Russia and the EU FTA. The number of topics that seems to best capture both CU and FTA exclusively is a K of 10. According to the diagnostic values reported in the appendix, this model with 10 topics does not have a perfect fit to the data. However, it captures well the substantive measure we are interested in. This is a typical trade-off using topic models: not always does the model with the best technical fit also provide the most intuitive and/or interpretable topics (Lucas et al., 2015). Using K larger or equal to 25 provides a very good model fit, but slices up topics unnecessarily. For instance, a high number of topics like 30, 40, or 50 finds single topics for European Parliament discussions of the FTA and meetings between the Commission and Ukrainian officials.[36]

However, we want these to be represented by a more general EU-Ukrainian trade topic. We show in the main text that high values in our EU-FTA and RU CU topic proportions correspond to both the actual development of general trade relations between Ukraine and the EU/Russia and

[36]We also calculate the STM for a K of 20, which has a significantly better model fit. The monthly topic proportions are very similar to the ones we report below. The correlations between the chosen topics from a topic model with 10 and 20 topics are 0.83 and 0.74 for the EU FTA and the CU, respectively.

that the press releases which score high on these topics are indeed about the EU FTA and the CU, respectively.

Figure A3: Cross-Validation for the Structural Topic Model



We show the *mean topic prevalence per month* in Figure (A4). Although being very volatile, the topic proportions approximate the development of the Ukrainian trade policy over the last 15 years: while in 2003, the topic of forming a customs union with Russia dominated the economic news, relative to the EU FTA topic. The prevalence of CU topic gradually declined before it almost completely disappeared from the policy discussion in 2014 when the FTA with the EU was signed. We also see the two time periods when only few or no articles where available in Nexis, in 2006, and in 2011. As the estimated topics represent the relative prevalence over time, this is not an issue for the estimation process, though. In 2011, both topics are equally affected by missing data, and the low number of articles in 2005-2006 still leads to the topics being estimated correctly relative to each other. Figure A5 below shows the raw data with weekly frequency.

Figure A4: Mean topic prevalence per month for EU FTA and the RU CU topic, 2003-2017.

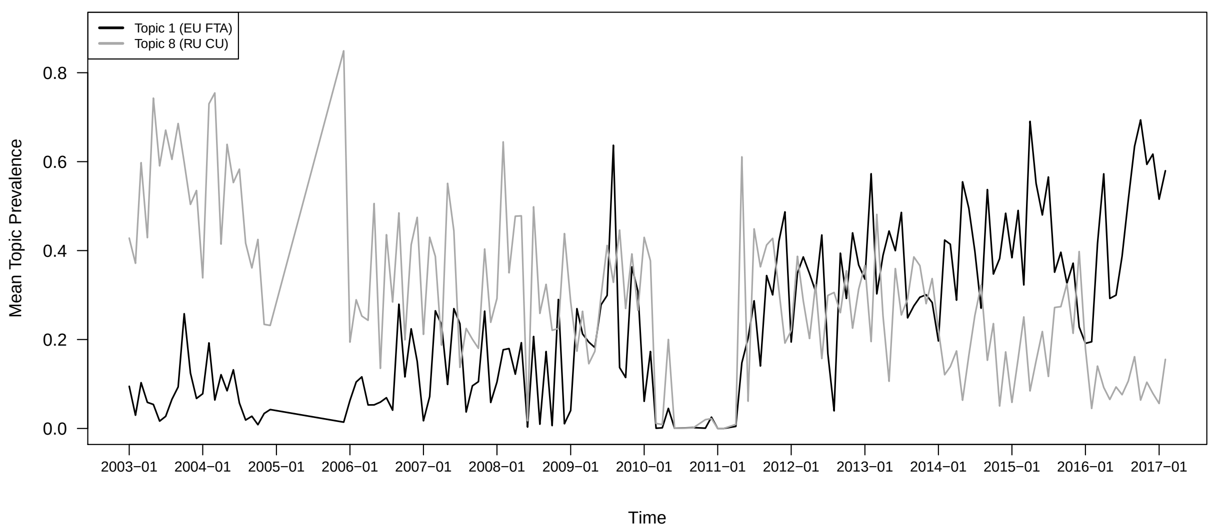
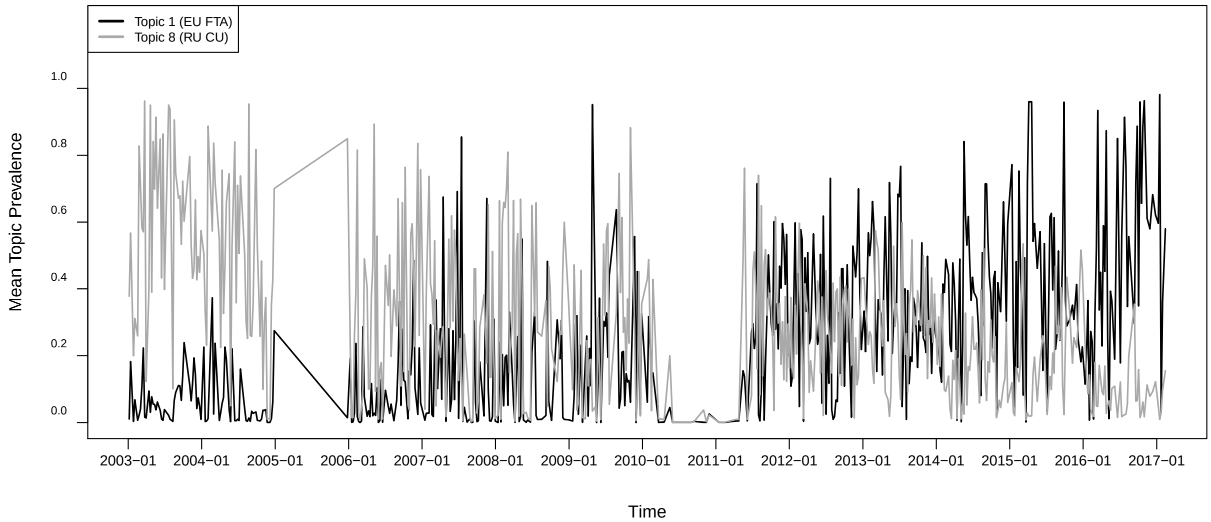


Figure A5: Mean topic prevalence per week



We also test for non-stationarity of our TPU measures and reject it in both cases, regardless of whether we include a trend or not. However, both series have strong autocorrelation patterns. For the monthly data, Table A2 presents estimations for AR(3) processes and also VAR model where we look how the two topics are influencing each other. Lags beyond the third one are not significant. We also fitted ARIMA models and found no evidence of moving average components in both cases.

Table A2: Time series analysis of topics

	(1)	(2)	(3)	(4)
Dependent variable	p^{EU}	p^{CU}	p^{EU}	p^{CU}
Model	AR(3)	AR(3)	VAR	VAR
L.p^{EU}	.285**		.241**	-.053
	(.07)		(.08)	(.08)
L2.p^{EU}	.261**		.220**	.025
	(.08)		(.08)	(.08)
L3.p^{EU}	.294**		.261**	-.017
	(.08)		(.08)	(.08)
L. p^{CU}		.070	-.012	.150
		(.06)	(.08)	(.08)
L2. p^{CU}		.411**	-.009	.387**
		(.08)	(.07)	(.07)
L3. p^{CU}		.353**	-.147*	.306**
		(.07)	(.07)	(.07)
ADF	-5.994	-7.350		
p-value	.000	.000		
N	146	146	133	133

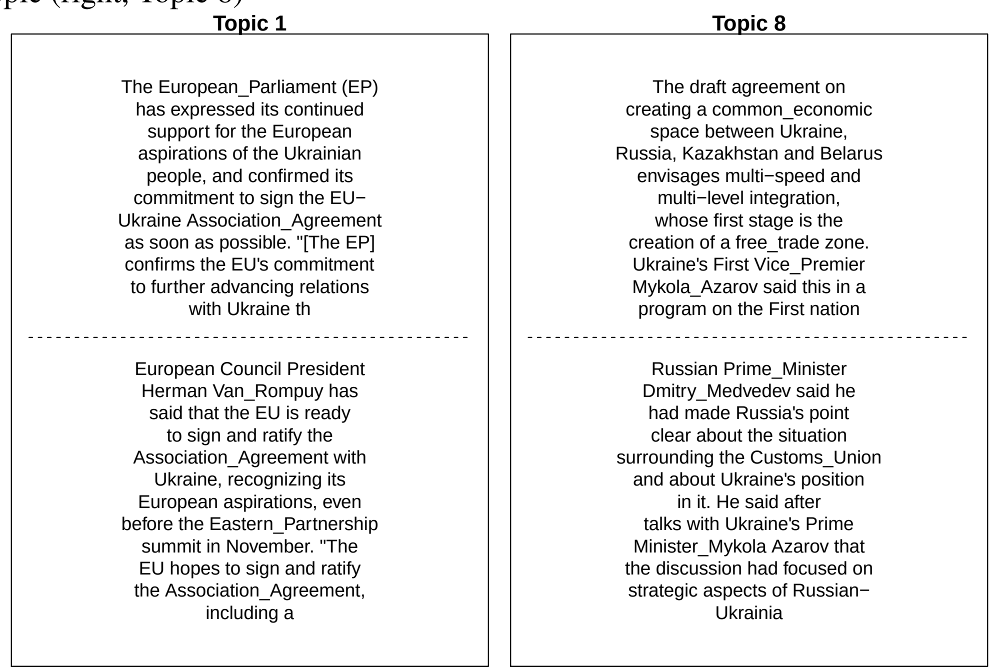
* p<0.05, ** p<0.01

Standard errors in parentheses. Columns (1) and (2) report point estimates of AR(3) models for corresponding series. Columns (3) and (4) present point estimates of a VAR model. ADF is the value of the Dickey Fuller test statistics without trend or drift with the corresponding p-value below. The null hypothesis is that the variable contains a unit root, and the alternative is that the variable was generated by a stationary process.

A5 Validity of the Quantitative Text Measure of TPU

A way to validate the topic model chosen here is to look at press releases which exhibit high proportions of the respective topics. Do these documents refer to the EU FTA and the RU CU, respectively? Figure A6 below shows two snippets from example articles with high topic proportions on EU FTA and Russian CU topics. One can see that press releases with high proportions of the topics estimated above do indeed discuss the EU FTA and the RU CU, respectively. The press releases identified as belonging to the EU FTA topic are about EU institutions and the progress of the Association Agreement with Ukraine, whereas the press releases belonging to the CU topic are about the customs union and the common economic space between Russia, Ukraine, Belarus, and Kazakhstan. This does not mean that the respective press releases are only about the EU FTA or the CU with Russia as documents can consist of a mixture of topics.[37]

Figure A6: Example Articles with high topic proportions for the EU FTA (left, Topic 1) and the RU CU topic (right, Topic 8)



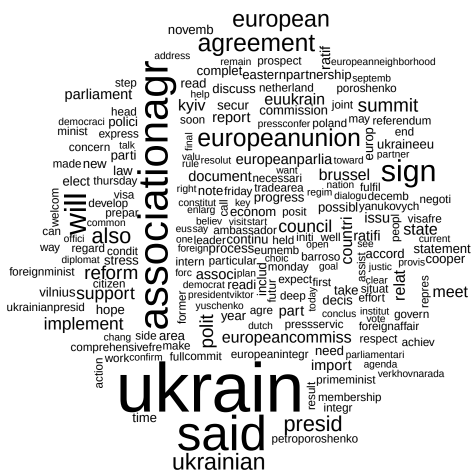
Below in Figure A7 we also provide wordclouds for the two topics, with EU FTA in black and RU CU in gray. The clouds show words that occur with a high probability, and the size of the words relates to the probability of a word to occur in the text collection, given the respective topic.

Given that there are other measures of policy uncertainty like the one developed by Baker et al. (2016), why are we using a new measure? First, while both measures rely on news coverage,

[37] In Appendix 1.3, we also plot word clouds of these two topics.

Figure A7: Word Clouds for EU FTA and RU CU topics. The size of the words refers to the probability of a word, given the topic.

Topic 1: EU FTA Topic

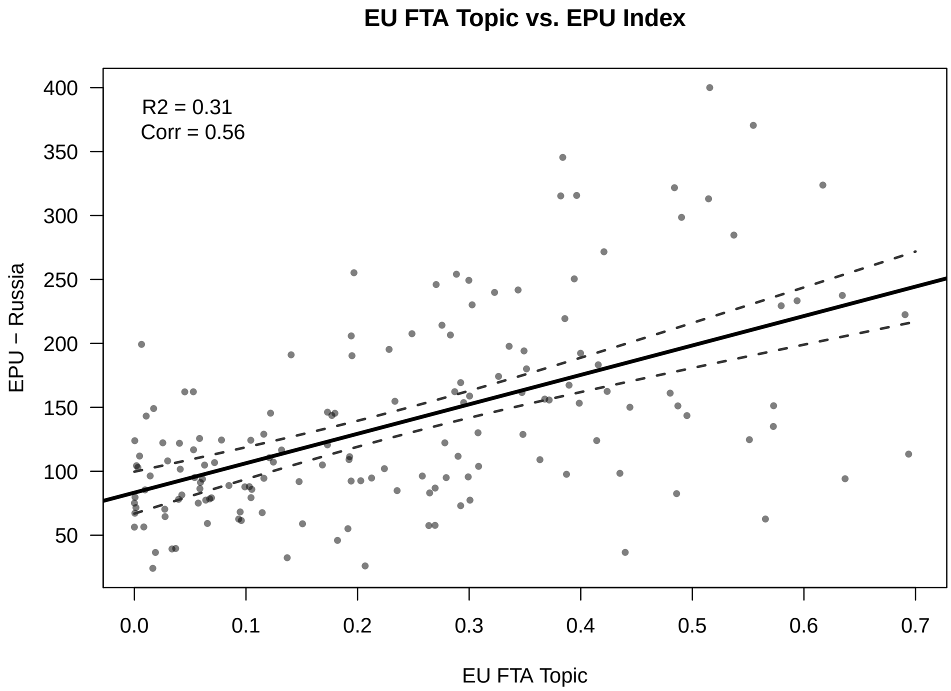


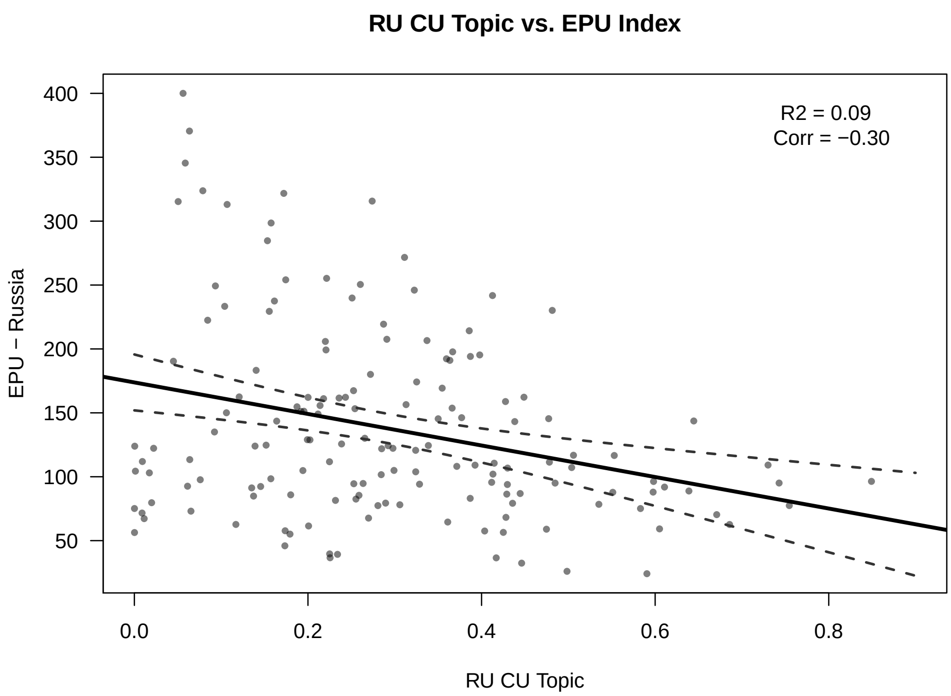
Topic 8: RU CU Topic

we do not use a pre-defined dictionary of terms related to uncertainty like the Economic Policy Uncertainty (EPU) index. The STM does only require us to specify the number of topics, but no pre-defined keywords or dictionaries. Second, we do not measure general economic uncertainty, but *trade policy uncertainty* for *specific* and substantively important *trade policy event*s between *specific trade partners*. The decision between a CU and the EU FTA is not captured by broad economic policy uncertainty. The EPU index picks up any kind of uncertainty and does not differentiate between global events (financial crisis), domestic uncertainty-inducing events (policy reforms), or specific events in relation to particular partners (e.g. Russian stop of gas exports, or threats thereof). In contrast, our measure picks up likelihood of changes in a specific trade policies with respect to particular countries/entities (Russia vs. EU). The interpretation of topic probabilities as uncertainty is derived from the fact that the two events (FTA vs. CU) are theoretically incompatible with each other and (even if compatible to a certain extent) not politically feasible at the same time. In a nutshell, our measure enables us to test predictions about uncertainty with respect to a specific policy vis-a-vis specific partners of Ukraine in the realm of trade - all three of which cannot be achieved by using the EPU index.

Despite these conceptual and empirical differences between ours and the Baker et al. 2016 measure, the reader might still want to compare the two measures. Ideally, we would compare our CU and FTA topics over time with a Ukraine-specific economic policy uncertainty index. However, Baker et al. have not developed the economic policy uncertainty index for Ukraine yet. In the absence of EPU for Ukraine, we plot our measures of EU FTA and RU CU probability against the EPU for Russia, shown in Figure A8 below. From a Russian perspective, a higher EU FTA probability should mean higher economic policy uncertainty (challenging Russian regional foreign policy), and a higher CU probability should be associated with lower uncertainty (strengthening Russian regional foreign policy). The EU FTA measure correlates positively with the Russian economic uncertainty measure, indicating higher uncertainty when an EU FTA with Ukraine becomes more likely. The CU topic is inversely correlated with Russian economic uncertainty, but only weakly so. This makes sense if EU-Ukrainian trade relations are indicative of EU-Russian relations, and that this relationship is one determinant of the economic policy index for Russia. Russian economic policy uncertainty can only be a proxy for a potential Ukrainian economic policy uncertainty, but signs and the strength of the relationships are in line with our expectations, and add some face validity to our measure.

Figure A8: Trade Policy Uncertainty (TPU) vs. Economic Policy Uncertainty (EPU) Index Baker et al. (2016)



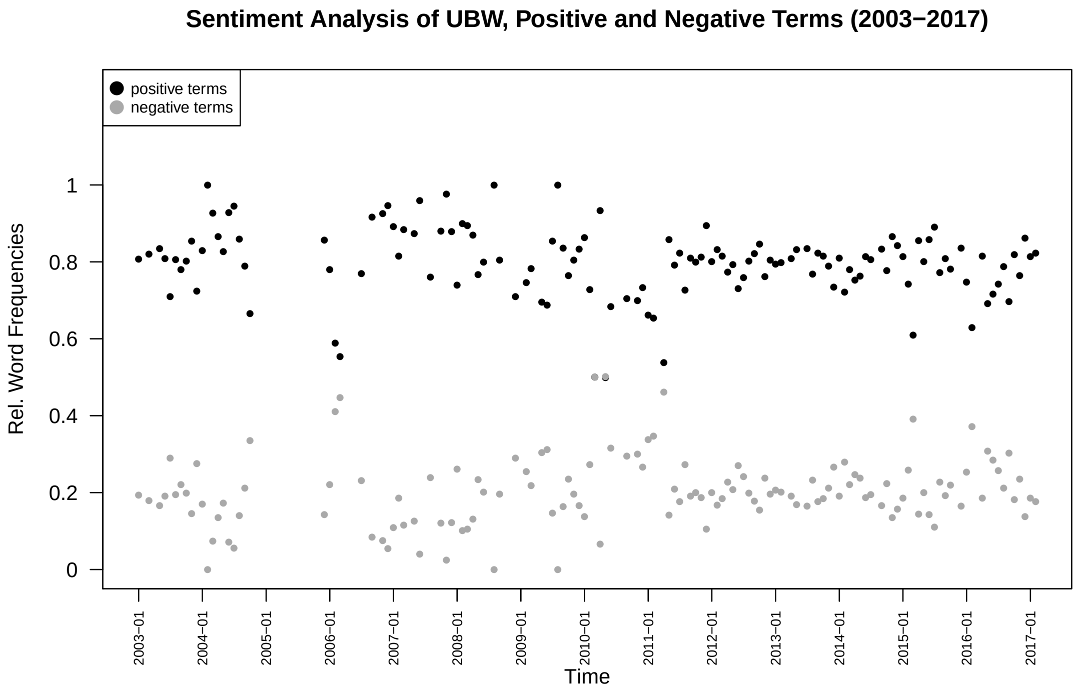


A6 TPU and Change in Text Tone/Sentiment

It could be a concern that UBW reports generally more negatively about the EU FTA than about the RU CU. Political Economy research has shown that newspapers can have considerable political bias, often driven by the demand factors like political ideology of readers (Gentzkow and Shapiro, 2010). In our case, we would be worried if our measure would only reflect change in sentiment or tone in the news releases over time. This concern is mitigated to a certain extent because are using an economic news release service, rather than daily newspapers. Compared to news papers articles, standard in press release services like Reuters concentrate on the content of news, strip away evaluative language By conducting a so-called *sentiment analysis* of the news releases, we show that the tone of UBW releases is always more positive than negative, but is constant across time and topics. Sentiment analyses describe the emotional state or mood of written text (Gonçalves et al., 2013). Here, we use a very simple, lexical-based approach applying pre-defined dictionaries of positive and negative terms. A number of different dictionaries for the English language exist, including commercially available dictionaries like the Linguistic and Word Count (LIWC) program. We use a freely available dictionary developed by Theresa Wilson, Janyce Wiebe, and Paul Hoffmann at the University of Pittsburgh (Wilson et al., 2005). The results are shown below.

The principle of this sentiment analysis is straightforward. We first take our collection of UBW press releases between 2003 and 2017, and apply two dictionaries to it: one dictionary with about 3900 negative English words and one with about 2200 positive words. Positive and negative connotations of words were developed by linguists and are described in depth in (Wilson et al., 2005). Then, we calculate the relative frequencies with which positive and/or negative terms occur in each single press release. Below in Figure A9, we plot the result of this exercise, where the X-axis indicates the respective month of publication and the Y-axis indicates the word frequencies of positive and negative terms (i.e., positive or negative terms divided by the sum of positive and negative terms) per month. The plot shows two results. First, regardless of the time period, there are always more positive than negative terms used in the press releases used in our further analysis. Second, the use of positive relative to negative terms is quite constant over time. While there is less variability in the relative frequencies (because there are more articles later on), there is no huge decline or increase of either positive or negative sentiment over time. This shows that the use of evaluative terms is stable over time: if there is a bias in terms of negative or positive reporting, it does not change dramatically over time.

Figure A9: Positive and negative sentiment in Ukraine Business Weekly articles



Another concern in relation to word use is that word choice *within topics* could be varying over time. For mitigating some of these concerns, we also do the sentiment analysis from above for articles with high topic proportions of both of EU FTA topic and the RU CU topic. Below, we plot the same graph as above, but restrict the sample of documents to those with topic proportions higher than the 75th percentile of the overall distribution of the respective topic. This reduces the sample of articles from UBW to 569 for both topics, but still leaves enough variation over time. One can see that the picture does not change from looking at the whole sample. Over time, positively and negatively connotated terms are quite constant, both in the whole sample of articles and in articles which are very highly related to either the EU FTA or the RU CU. This result holds for other thresholds such as median or mean topic proportions. This supports or assertion that the news releases from Ukraine Business Weekly do not change tone or sentiment substantively over the time period of investigation.[38] Moreover, it is not the case that articles discussing the EU FTA are generally more positive in tone than articles discussing the RU CU.

[38]Note that this could look quite different if our news source would be daily newspapers. Since the reporting in press releases is rather technical, it is not surprising that there is no change in positive or negative tone over time.

Figure A10: Positive and negative sentiment in Ukraine Business Weekly articles. Here, sentiment analysis was conducted only articles with topic proportions for EU FTA (left) and RU CU topic (right). The articles used have topic proportions larger than the 75th percentile of the respective topic