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Trade Policy Uncertainty and its Effect on Foreign Direct Investment: Evidence from Mexico*

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Abstract: This paper investigates whether "trade policy uncertainty" (TPU), even absent changes in actual policy, may have an adverse effect on foreign direct investment. The paper focuses on the case of Mexico, where we observe a plausibly sharp and exogenous increase in TPU vis-à-vis a large trading partner beginning in the second half of 2016. To test this hypothesis, we use data from Google Trends to construct a TPU index and argue that this index adequately captures both time series and cross-sectional variation in TPU across states in Mexico. We exploit this variation to identify the effect of increased uncertainty on FDI flows. We find that the increase in TPU was associated with a negative effect on FDI inflows, with the effect being driven by the negative impact that TPU had on FDI in export oriented states.

Keywords: trade policy uncertainty, foreign direct investment, real options.
JEL Classification: F40, F62, F21

Resumen: Este documento investiga si la "incertidumbre sobre la política comercial" (IPC), incluso sin que se hayan efectivamente dado cambios en dichas políticas, puede tener un efecto adverso sobre la inversión extranjera directa. El documento se enfoca en el caso de México, donde observamos un aumento grande y exógeno en la IPC vis-à-vis un socio comercial grande a partir de la segunda mitad de 2016. Para probar esta hipótesis, usamos datos de Google Trends para construir un índice de la IPC y argumentamos que este índice captura adecuadamente tanto la variación temporal como transversal en la IPC en todos los estados de México. Explotamos esta variación para identificar el efecto del aumento en la incertidumbre sobre los flujos de IED y encontramos que el aumento en la IPC afectó negativamente los flujos de IED, siendo este efecto el resultado del impacto negativo que la IPC tuvo sobre la IED en estados con orientación exportadora.

Palabras Clave: incertidumbre sobre política comercial, inversión extranjera directa, opciones reales.

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1. Introduction

Economists have always had an interest in understanding how uncertainty affects decision making and macroeconomic variables. The relationship between uncertainty and economic outcomes is not straightforward, as there are theoretical mechanisms through which uncertainty may have either a positive or negative effect on economic variables of interest.[1] The expected sign of the effect of greater uncertainty on economic outcomes may depend on various details of the decision problem faced by economic agents.[2] In general, for forward-looking agents with rational expectations the effect of greater uncertainty on current decisions will depend on the presence (or absence) of sunk and/or adjustment costs, the exact nature of uncertainty faced by the decision-maker, and whether current decisions have an effect on expected future returns.[3] From a theoretical point of view, the real options perspective on decision making has been the benchmark framework to think about how uncertainty affects the actions of economic agents in dynamic decision problems (see Dixit [1989] and Dixit and Pindyck [1994]). For example, in the case of investment decisions the common view is that due to the presence of adjustment costs that make current decisions hard to reverse, greater uncertainty makes economic agents more cautious and they optimally decide to postpone the investment decision, since by delaying investment they gain the *option*

[1] For example, see Caballero [1991] for a classic exposition on the complicated nature of the investment-uncertainty relationship. In particular, Caballero identifies conditions under which the investment-uncertainty may not have the 'expected sign' (i.e. increased uncertainty may lead to more investment). For theoretical models that propose mechanisms through which uncertainty affects decision making, and thus macroeconomic variables, see Abel [1983], McDonald and Siegel [1986], Dixit [1989], Basu and Bundick [2017], Leduc and Liu [2015], and Fajgelbaum et al. [2017] among others.

[2] See Dixit and Pindyck [1994] and Stokey [2008] for a general discussion of dynamic decision problems under uncertainty and Bloom [2014] for a general discussion of the channels through which uncertainty can affect firm and consumer behavior.

[3] For example, the decision to invest today in technology upgrading or not may affect the opportunity to exploit export opportunities that present themselves tomorrow given that exporting is an activity associated with strong selection effects whereby only the most productive firms may exploit the opportunity to sell their goods in foreign markets. Alternatively, consider a firm that delays R&D efforts today. Then this may affect the returns to R&D tomorrow if these returns depend on securing a patent, since delaying investments in R&D reduces the probability of being the first to patent an innovation.

to make this decision when the economic environment is more favorable or when they have better information regarding the returns to investing.[4]

It has not been until recently that there has been a surge in the academic literature regarding the quantification of uncertainty on behavior due to the increased availability of empirical proxies for uncertainty (see Bloom [2014] for an overview). One key area where our knowledge is still very limited concerns the effects of *trade policy uncertainty* on economic outcomes. Notable exceptions include Handley [2014], Handley and Limao [2015], Pierce and Schott [2016], Feng, Li, and Swenson [2017], and Handley and Limao [2017], who study the effects of *reductions* in trade policy uncertainty. The cases studied by these authors involve reductions in trade policy uncertainty that arise from a country entering into a free trade area (Handley and Limao [2015]) or China entering the WTO (Pierce and Schott [2016], Handley and Limao [2017], and Feng et al. [2017]). As such, their main focus is on the effects of reductions in *tariff uncertainty* that result from the enactment of the agreements. For example, Handley and Limao [2017] report that Chinese exporters faced uncertainty regarding the tariffs they would face in the US market given that if China had not been granted most favored nation (MFN) status by the US Congress in 2000 it could have faced an average tariff of 31 percent rather than the average US MFN tariff of 4 percent. China's accession into the WTO effectively eliminated this uncertainty, and Handley and Limao [2017] find that this resulted in greater entry of Chinese exporters into the U.S. market. Feng et al. focus on the exit from and entry into exporting that was observed among Chinese firms after the reduction in tariff uncertainty. They find that, on average, entering firms offered higher quality and lower prices than exiting firms. Handley and Limao [2015, 2017] study the effects that reductions in trade policy uncertainty had on firm-level investment and export

[4] However, the effect of greater uncertainty on investment can be a priori uncertain. In a classic paper on dynamic investment decisions, Caballero [1991] shows that the sign of the investment-uncertainty relationship may be either positive or negative depending on market structure (perfect vs imperfect competition) and the returns to scale in production: investment and uncertainty can be positively correlated, even in the presence of irreversible investment, if firms face very elastic demand curves and returns to scale are non-decreasing. Similarly, Sarkar [2000] considers a canonical real options model of investment and shows that the probability of investing is non-linear in the volatility (i.e. uncertainty) of the earnings process from investing faced by firms.

market participation decisions. They find that reductions in tariff uncertainty faced by firms induced greater investment and entry into exporting.

Our paper contributes to the existing literature on the effects of trade policy uncertainty by studying the case of an *increase* in trade policy uncertainty (TPU) for a small open developing economy vis-à-vis a large trading partner. The recent push towards more protectionist policies in industrialized economies has led to an environment of increased uncertainty about future trade policies. In particular, Mexico experienced a significant increase in TPU beginning in the second half of 2016 owing to the fact that the U.S., its main trading partner by far, argued for the need to renegotiate the North American Free Trade Agreement (NAFTA). Given that NAFTA represented much more than a tariff reduction scheme, as it also provided an institutional arrangement to promote trade and investment flows among its members, trade policy uncertainty in this case involved the future of non-tariff barriers faced by exporters in the region, particularly those serving the U.S market, in addition to tariff uncertainty. However, it can be argued that tariff uncertainty in the context of NAFTA was relatively limited. Indeed, before the USMCA, Mexico would have faced, on average, low tariffs for exports to the United States under the most favored nation (MFN) treatment. Additionally, not all exporters in Mexico make use of the tariff advantages of NAFTA in order to export to the US: in 2016 more than 50 percent of Mexican exports to the US occurred outside the purview of NAFTA.[5] Thus, the nature of trade policy uncertainty that we analyze goes far beyond tariff uncertainty. However, we share with the existing literature the fact that changes in trade policy uncertainty stem from the way in which the existence, or lack thereof, of trade agreements affects bilateral trade relationships.

In order to capture the fact that uncertainty in the context of NAFTA goes beyond tariff uncertainty, as opposed to previous literature that has relied on the gap between effectively applied tariffs and bound tariff levels as a proxy measure for trade policy uncertainty, we propose a more direct measure of TPU based on Google trends in a fashion similar in spirit

[5] Using data from the US Department of Commerce we estimate that in 2016 55.6% of Mexican export to the US used the tariff preferences provided by NAFTA. Similarly, we estimate that for 2016 48.9% of Mexican imports from the US entered Mexico using the tariff advantages of NAFTA.

to the economic policy uncertainty index of Baker et al. [2016]. Indeed, we believe that this measure has the advantage of being a more direct measure of trade policy uncertainty and that it encompasses both tariff and non-tariff trade policy uncertainty for this particular episode. We construct the TPU index for the period 2012-2018 and we observe a sharp, plausibly exogenous, increase in uncertainty starting in mid-2016.[6] By constructing this TPU index individually for each state in Mexico we are able to exploit both time-series and cross-sectional variation in trade policy uncertainty to identify the causal effect of higher levels of uncertainty on foreign direct investment and export participation. However, it is important to acknowledge and emphasize that the construction of our TPU index is specific to the particular circumstances of Mexico during the period under consideration and leans heavily on our prior knowledge regarding the nature and source of the increase in policy uncertainty during this period. Specifically, based on the argument that "bad news" is synonymous to an increase in uncertainty (see Bloom [2014]), we are able to interpret increases in our TPU index as reflecting an increase in uncertainty given our knowledge regarding news about trade policy in Mexico. Thus, our TPU index is not a general trade policy uncertainty index for Mexico and a direct application of such a construction in other contexts would not necessarily be appropriate.

Having constructed a TPU index for Mexico vis-à-vis a large trading partner, we use it to analyze the effects of trade policy uncertainty on foreign direct investment. We take as our benchmark the standard view, mentioned above, of dynamic investment problems.[7] In this case, due to the presence of adjustment costs in investment, greater uncertainty regarding the expected returns to investing will make investors more cautious regarding an action that is not easily reversible in the short-run.[8] Thus, foreign investors will delay investment decisions

[6] We focus on the period 2012-2018 because this is the period for which Google Trends data allows us to calculate our TPU index at the state level.

[7] We take the "standard view" to be the real options perspective in which the presence of adjustment costs in investment decisions implies that an increase in uncertainty entails a postponement of investment projects as investors optimally chose to exercise their "option" to wait until the economic environment turns more favorable and/or they obtain better information regarding the returns to investing.

[8] Adjustment costs may be either the standard quadratic adjustment costs typical of the investment literature or the extreme case of irreversible investment as discussed in Dixit and Pindyck [1994].

until the economic environment becomes more favorable and/or they are able to acquire more precise information regarding the distribution of returns to investing.[9]

We combine our state-level TPU index with state-level data on foreign direct investment into Mexico to analyze how changes in trade policy uncertainty may have affected FDI flows. To identify these effects, our estimation framework exploits both time-series variation in TPU and its variation across states in Mexico. Our main finding lends support to the standard view of the investment-uncertainty relationship previously discussed. That is, our estimates indicate that the large increase in TPU that was observed beginning in the second half of 2016 was associated with a negative effect on FDI flows, with the effect being driven by the negative effect that TPU had on foreign direct investment in states that are more export oriented. In particular, we find that increased trade policy uncertainty has had an economically sizeable effect in terms of discouraging FDI flows into Mexico. We estimate that, everything else equal, in the absence of the uncertainty regarding the future of NAFTA, Mexico would have received an additional 15.2 to 15.5 billion dollars in foreign direct investment between the first quarter of 2016 and the last quarter of 2018. To put these estimated losses in context, we note that they are roughly equivalent to 2.5 times the total FDI received by the Mexican automotive sector in 2015 or roughly 78 percent of the accumulated FDI by this sector between 2011 and 2015.[10] This suggests that an important mechanism through which free-trade agreements, such as NAFTA, influence economic activity is by providing certainty for investors.

The rest of this paper is organized as follows: section 2 details our construction of the measure of trade policy uncertainty that will be used in the econometric specifications of section 3. Section 3 presents our results for the effects of trade policy uncertainty on foreign direct investment. Section 4 concludes.

[9] In the appendix we present evidence regarding the effect of uncertainty on export participation decisions, and how this relates to the real-options perspective on decision making under uncertainty.

[10] Total FDI received by the Mexican automotive sector in 2015 amounted to 5,757 million dollars. The accumulated FDI by this sector between 2011 and 2015 was equal to 19,783 million dollars. (http://www.promexico.mx/documentos/biblioteca/la-industria-automotriz-mexicana.pdf)

2. Measuring Trade Policy Uncertainty

In this section we detail the construction of the measure of trade policy uncertainty (TPU) that will be used in the empirical specifications of section 3. One of the difficulties in quantifying the causal effect of uncertainty on the economy has been the lack of useful proxies to be used in empirical analysis. In part, this difficulty owes to the very definition of uncertainty itself. Since the work of Knight [1921] economists have distinguished between *risk* (randomness that can be cast in terms of a probability model) and *uncertainty* (randomness that is immeasurable and for which agents cannot come up with a probability model). Thus, under Knightian uncertainty agents are unable to forecast the likelihood of events happening. Despite the conceptual difference between these two concepts, in most empirical applications measures of uncertainty will inevitably reflect both risk and Knightian uncertainty.

The difficulties associated with the measurement of uncertainty notwithstanding, much has been learned in recent years thanks to the wider availability of both macro and micro data that can be used to elicit the uncertainty faced by economic agents. Common measures of uncertainty that have been proposed in the literature include the volatility of the stock market (i.e. the VIX index which measures the market's expectation of volatility over the next 30 days), the dispersion of productivity shocks to firms, forecaster disagreement,[11] and the uncertainty of forecasters regarding their own forecasts (subjective uncertainty). In recent work, Jurado et al. [2015] propose a measure of time-varying macroeconomic uncertainty based on the forecast errors of a forecasting model that includes a large set of economic variables; the idea being that times in which economic variables become harder to forecast reflect greater underlying uncertainty. In this sense, their definition captures part of the original definition of Knightian uncertainty. Interestingly, these authors find that their proposed measure of uncertainty fluctuates rather differently and often displays less time-series volatility than the previously-mentioned measures used elsewhere in the literature.

[11] The intuition here is that periods when professional forecasters hold a more diverse set of opinions are likely to reflect greater underlying uncertainty regarding the future course of the economy.

Among the wide set of measures of economic uncertainty that have been proposed in the literature, the news-based measure proposed by Baker et al. [2016] has been one of the most influential. These authors originally constructed an index of economic policy uncertainty (EPU) for the US based on the frequency of articles in 10 major U.S. newspapers containing the following trio of terms: 1. "economic" or "economy"; 2. "uncertain" or "uncertainty", and 3. One or more of "Congress", "deficit", "Federal Reserve", "legislation", "regulation" or "White House". Analogous indices are currently available for 24 countries, covering both developed and developing economies and economies in every continent, and is widely followed by policymakers.[12] Our measure of trade policy uncertainty (TPU) is inspired by the work of Baker et al. [2016], though it differs importantly in ways that we will now describe.

To construct our trade policy uncertainty index, we rely on data from Google Trends rather than on news-based mentions as in Baker et al. [2016].[13] Google Trends reports weekly data on the frequency with which given terms are contained within the search queries initiated by Google users. Data from Google Trends for specific search terms, which may include one or more words, is reported in a scale that goes between 0 and 100, taking a value of 100 on the date in which a given term is searched-for the most within the reference period. Values under 100 are defined in relation to the date of maximum search. For example, if the Google Trends index for the word "NAFTA" reports a value of 100 on the first week of January 2017, then some other date with a value of, say, 50 corresponds to a date where the word "NAFTA" was searched for half as much as on the first week of January 2017. A value of 0 implies a popularity of less than 1% relative to the value of 100. We constructed a weighted average of the Google Trend index for different search terms related to NAFTA and the US-Mexico trade relationship. Specifically, our search terms include the words "NAFTA", "TLCAN", "NAFTA Trump", "TLCAN Trump Mexico", and the Spanish terms for "renegotiation", "NAFTA renegotiation", "tariff", "free trade", and "what is NAFTA". The weights were

[12] The EPU index of Baker et al. can be consulted at http://www.policyuncertainty.com or in data sources widely used by policymakers such as Bloomberg, Haver, Reuters, and FRED.

[13] Castelnuovo and Duc Tran [2017] use Google trends to construct an uncertainty index, not specific to any one policy dimension as we do here, for both Australia and the US. They show that their Google based index is positively correlated to alternative proxies for uncertainty available for those countries.

chosen subjectively to reflect our priors on the relevance of these terms, but also in such a way that coupled terms such as "NAFTA Trump" or "NAFTA renegotiation" receive more weight than single terms like "NAFTA" or "renegotiation".[14] The index is constructed on a weekly frequency. Since the econometric specifications of section 3 will use quarterly data, we aggregate the TPU index to that frequency by taking the average over the weeks comprised by the period in question.[15]

An important point worth noting is that, in contrast to Baker et al. [2016], nowhere in our search criteria do the words "uncertain" or "uncertainty" appear. This may strike the reader as odd given that a key aspect of the methodology of those authors is to count news articles where these two words can be found together with other relevant search criteria defined by the authors. However, note that for the purposes of this paper we only require that our TPU index capture the degree of trade policy uncertainty for Mexico in a period in which we know that trade policy uncertainty has increased. This allows us to incorporate prior knowledge about the source of trade policy uncertainty in defining the relevant terms to be included in the construction of the index. In particular, in lieu of the words "uncertain" or "uncertainty", the specifics of this period, at least where trade policy is concerned, allows us to use terms such as "Trump" in combination with other words related to NAFTA as proxies for uncertainty related to trade policy.[16] Thus, our TPU index mainly reflects the increased uncertainty associated to the specific outcome related to the renegotiation of NAFTA and the rules governing bilateral trade and investment flows in North America.

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[14] The weights for the index used throughout this paper are

$$\begin{aligned} Index = {} & 0.1(NAFTA) + 0.1(TLCAN) + 0.05(renegotiation) + 0.2(NAFTA\ renegotiation) \\ & + 0.05(tariff) + 0.15(NAFTA\ Trump) + 0.15(TLCAN\ Trump\ Mexico) \\ & + 0.1(free\ trade) + 0.1(what\ is\ NAFTA) \end{aligned}$$

Alternative weighting schemes, such as equal weighting, yielded qualitatively similar indices as the one reported in the main text.

[15] For example, the TPU index for the second quarter of 2014 corresponds to the average of the weekly TPU index for the weeks contained in that quarter.

[16] Considering that the increase in trade policy uncertainty since 2016 can be traced back to the rhetoric of the then candidate and now president Donald Trump, we argue that including the term "Trump" together with other trade related keywords in our search parameters will be indicative of the uncertainty related to trade policy matters embedded in Google searches generated by users during the reference period.

It is also worth pointing out that both the construction and the interpretation of movements in our TPU index rely heavily on our prior knowledge regarding the source and nature of uncertainty affecting Mexico during the period under consideration. Increases in our TPU index are interpreted as reflecting increases in uncertainty due to the overall negative tone of news report regarding the US stance on trade policy in general and on the US-Mexico relationship in particular during our reference period. Thus, our approach to the construction and interpretation of a trade policy uncertainty index is specific to Mexico for the period 2012-2017, and an analogous implementation in other instances would require additional knowledge regarding the circumstances that explain the movements in a similarly constructed TPU index.

Figure 1 emphasizes the initial burst in trade policy uncertainty by presenting the 6-week moving average of our TPU index for the period January 2012 to July 2017. It can be easily appreciated that from its relatively low level all throughout 2015, our TPU index starts displaying a strong upward trend from 2016 onward. In particular, as is the case with the EPU index of Baker et al. [2016], our TPU index spikes at specific dates that can be reasonably associated with moments of heightened trade policy uncertainty for Mexico, such as the date of the US presidential election or the date in March 2017 when various news outlets reported that Donald Trump intended to serve notice on the US leaving NAFTA, and that these spikes correspond to much higher values for the TPU index relative to the values observed at the earlier part of the reference period.[17] As in Baker et al. we take the large time series variation in our TPU index around these known dates as a form of validation for our measure of trade policy uncertainty. Furthermore, Figure 1 also shows a similarly constructed TPU index for the United States and it is easily seen that trade policy uncertainty has also increased from the perspective of the US and that there is a strong correlation between both

[17] Notice that the rapid decreases in the index after the spikes should not be interpreted as immediate decreases in uncertainty. It is important to keep in mind that the index is constructed based on Google searches and there will naturally be decreases in these searches following the noted spikes in Figure 1 as other news stories take precedence and/or the intensity of interest on a particular news story decreases among the public. The spikes serve to identify key events that are driving uncertainty up or down. In that regard, the "increased volatility" that can be observed in Figure 1 in the second half of 2016 is reflection of the fact that there are more frequent news stories and more news outlets reporting on NAFTA and this is a topic of recurring interest in Mexico vis-à-vis an earlier period in which NAFTA related stories where infrequent and far between.

indices.[18] As an additional validation for our Google based index, we calculate news-based reference indices in the spirit of Baker et al. [2016] using mentions of the words “TLC” (i.e. NAFTA) and “Trump” in the main newspaper covers of national circulation in Mexico.[19] Figures A1 and A2 in the Appendix show the comparison of these indices with the Google trends index for the corresponding terms. Both news-based indices and Google based indices display similar qualitative behavior during the relevant time period. In particular, the news-based indices also show a significant increase in the popularity of the terms “NAFTA” and “Trump” from the second half of 2016 onwards. Exploiting the time-series variation in TPU will be an important part of our identifying strategy, which will be discussed in more detail in section 3.

A significant advantage of using data from Google Trends for the construction of our TPU index is that the aggregate index reported in Figure 1 can be similarly constructed for each individual state in Mexico. That is, for each state we construct a TPU index by applying the same procedure that was used to derive the TPU index for Mexico as a whole. Since there is regional heterogeneity across states in terms of their engagement with the global economy, we will exploit the cross-sectional variation in TPU across states in our identification strategy. Figure 2 relates the initial increase in TPU, calculated as the difference between average TPU in 2016Q3-2017Q1 and the average TPU in 2015Q3-2016Q2, to each state’s average share in total Mexican manufacturing exports. For export-oriented states, there is a positive relationship between engagement with the global economy and the change in trade policy uncertainty.[20] Figures 3 and 4 display the quarterly TPU index for all states for the period 2014-2018, as will be used for estimation for reasons discussed in section 3, grouping

[18] The actual correlation between the 6 week moving averages reported in Figure 1 is 0.85. The fact that trade policy uncertainty has increased in the US is corroborated by the news-based trade policy uncertainty index of Handley and Limao [2017].

[19] At the time of the writing of this document, Google searches recorded positive search activity for the term “TLCAN”, but not for the term “TLC”. For newspapers, the term “TLC” covers the results for both “TLC” and “TLCAN” as they are taken to be perfect substitutes for news coverage in the Mexican media.

[20] A state is said to be export-oriented if its average share in manufacturing exports is above the median value across all states (average for 2014-2015). The pattern that emerges in Figure 2 is also observed if export orientation is defined by whether the ratio of state manufacturing exports-to-state GDP is above or below the median value across all states. This occurs because in the Mexican economy there is a strong correlation between a state’s contribution to total exports and the contribution of those exports to state GDP: the correlation between the average share in manufacturing exports and the average state exports-to-state GDP ratio is 0.89.

states by export oriented (Figure 3) and non-export oriented (Figure 4). It can be seen that the variation in the aggregate TPU index for Mexico (Figure 1) is mostly driven by variation in TPU in export-oriented states. Figures 3 and 4 summarize the regional heterogeneity and time-series variation in TPU that will be exploited in the next section to identify the effects of trade policy uncertainty on foreign direct investment.

3. The Effect of Trade Policy Uncertainty on FDI and Export Participation

In this section we use the TPU index described in section 2 as the explanatory variable of interest in an econometric specification aimed at investigating the effect of heightened uncertainty on flows of foreign direct investment to Mexico. As was argued previously, this outcome is viewed as the result of the decisions of forward-looking agents that take into account possible adjustment and/or sunk costs that could induce non-trivial dynamics in the decision-making process given that actions taken today can affect returns tomorrow. In particular, it was argued that the effect of higher trade policy uncertainty on FDI flows could be expected to be negative, as foreign investors may choose to exercise their option to delay investment until they are able to obtain more precise information about the future returns to investing in Mexico.

In the remainder of this section we study the impact of trade policy uncertainty on flows of foreign direct investment. FDI flows are reported in millions of dollars at the state level and are available at a quarterly frequency.[21] To get a sense of the time-series and cross sectional variation in the FDI data Figure 5 plots the evolution of total foreign direct investment flows into Mexico between 2010 and 2018, while Figure 6 shows the regional distribution of total FDI inflows for the year 2015.[22] From Figure 5 it stands out that inflows of foreign direct investment display a seasonal pattern, with inflows concentrated in the first quarter of the year.[23] From Figure 6 we can see that there is a lot of heterogeneity in terms of how foreign

[21] The source for the data on foreign direct investment is the Secretaría de Economía (https://www.gob.mx/se/).
[22] We choose 2015 as a representative year that provides the most recent observation prior to the exogenous increase in TPU in 2016.
[23] Additionally, it is notable that 2013 stands out as an outlier both in terms of the large inflows of FDI that were received that year, and for the fact that the largest inflow occurred in the second rather than the first quarter.

investors allocate FDI across states in Mexico, typically concentrating their investments in the Center and Northern regions of the country, which are the most developed in terms of their manufacturing capability. We exploit these two sources of variation to estimate the effect of uncertainty on FDI for the period 2014-2018.[24]

Our baseline econometric specification for this exercise is given by

$$\frac{FDI_{s,t}}{GDP_t} = \beta TPU_{s,t} + \gamma Z_{s,t} + \eta_s + \eta_q + \eta_t + \varepsilon_{s,t}, \qquad (1)$$

where the dependent variable is state-level FDI as a share of national GDP.[25] The regressor of interest is $TPU_{s,t}$, trade policy uncertainty in state *s* at time *t* (using quarterly data), which corresponds to the four-quarter moving average of the quarterly TPU index described in the previous section (see Figures 3 and 4). This specification identifies the coefficient of interest (β) from both the time-series and cross-sectional variation in TPU. Our econometric model also includes state fixed effects (η_s) that control for time invariant state characteristics such as institutional quality, proximity to the US, or the skill composition of the workforce; fixed effects for the quarter in which FDI was received (η_q) to control for seasonal effects,[26] and time fixed effects (η_t) to control for common shocks to all states that may affect FDI flows, such as changes in foreign demand for Mexican exports or changes in the risk appetite of foreign investors, among other things. These fixed effects do not control for changes in time within each state that could affect the state's attractiveness as a destination for FDI. Given that our estimation sample only comprises the period 2014-2018 and that most of the structural characteristics of states would not be expected to change in such a short amount of

[24] We exclude 2012 and 2013 to avoid the anomalous behavior of 2013, in both timing and magnitude of inflows, and to be further removed from the Great Recession and the effect it may have had on FDI inflows towards Mexico.

[25] The natural estimating equation to consider would have had both the dependent and explanatory variables in logs. However, some observations for FDI entail negative values. To avoid dropping observations from our sample, and to avoid complicated transformations of the dependent variable, we decided to normalize state-level FDI with national GDP. We consider this the appropriate normalization since normalizing by some state-level variable (i.e. state-level GDP or manufacturing employment) would result in a measure of the importance of FDI in the state's economy, when what we care about is how much funds foreign investors decide to allocate to Mexico, regardless of their importance relative to the particular size of the economy of a state. Additionally, by dividing FDI flows by national GDP we can easily control for a common trend, as GDP growth is associated with more FDI inflows.

[26] We observe that FDI flows tend to be concentrated at the beginning of the year.

time, and are thus controlled for by the state fixed effects, our only remaining concern would be in relation to determinants of investment that may vary within state rather quickly. With this in mind, in the vector Z we include a variable to control for the heterogeneous changes in insecurity at the state level during the period of study, which is the only relevant determinant of FDI that met the criteria previously discussed. We proxy for insecurity with the homicide rate.[27]

Column 1 in Table 1 presents the results for our baseline specification. Consistent with our initial conjecture, we find that $\hat{\beta}$ is negative and statistically significant. That is, we find evidence that an increase in trade policy uncertainty has a negative effect on inflows of foreign direct investment. This result lends further support to the evidence on the negative investment-uncertainty relationship (see Bloom [2009], Baker et al. [2016], and Handley and Limao [2017], among others).

Motivated by Figure 2, we dig deeper into the results of our pooled regression (column 1, Table 1) by running our baseline specification on a split sample where the sample is divided according to the export orientation of states.[28] Notice that by running our baseline specification on a split sample rather than on the pooled sample that includes an interaction between independent variables and a dummy for export orientation we are allowing for the possibility that not only the marginal effects of the independent variables on the dependent variable vary across groups, but that error variances can also vary. Columns 2 and 3 in Table 1 present the results for export oriented and non-export-oriented states, respectively. We see that the negative and statistically significant effect of TPU on FDI found for the pooled regression is statistically significant only for the subsample comprised of export-oriented

[27] We obtain homicides by state through monthly police reports compiled by the Executive Secretariat of the National System for Public Security (http://secretariadoejecutivo.gob.mx/incidencia-delictiva/incidencia-delictiva-datos-abiertos.php). State populations by quarter are linear interpolations on yearly demographic projections by the National Population Council (http://www.conapo.gob.mx/es/CONAPO/Proyecciones_Datos). We then simply compute homicide rates per 100,000 persons at the state level. In the appendix we report regression results that proxy for insecurity with the crime rate, where the crime rate includes homicides, sexual assaults, injuries, kidnappings, etc. The results are largely unchanged with respect to those reported in the main text.

[28] Export oriented states are defined as those whose share in total manufacturing exports is above the median value across all states.

states. That is, the negative effect of TPU on investment is entirely driven by the effect that an increase in trade policy uncertainty has on FDI inflows directed toward export-oriented states.

The fact that the negative effect of trade policy uncertainty on flows of foreign direct investment is driven by what happens in export oriented states is a reflection of the fact that in Mexico foreign direct investment supports export activity in an important way.[29] Thus, it is natural that since export oriented states are the ones most exposed to the possibility of negative changes in the conditions for market access in the US, it would be the investment flows directed towards these states the ones that are most affected by trade policy uncertainty and the "wait and see" effect that it induces on investment decisions.

To get a sense of the magnitude of our estimate of $\hat{\beta}$, the marginal effect of TPU on the dependent variable, and the amount of foreign direct investment that would have entered the Mexican economy in the absence of an increase in trade policy uncertainty, we consider the following counterfactual exercise: suppose that from 2016 onwards trade policy uncertainty had remained at its average level for 2014-2015 in each state, then how much extra foreign direct investment would we have seen flowing into the Mexican economy? FDI flows during the 2016-2018 period registered levels similar to those observed in 2015. However, it would be incorrect to conclude that trade policy uncertainty had no impact on flows of foreign direct investment in Mexico. Instead, to assess the impact that an increase in trade policy uncertainty had on foreign direct investment, we need to know how FDI flows would have looked like had there been no increase in TPU.

For each state s let $\overline{TPU}_s$ denote the average TPU for 2014-2015 and let $\hat{y}_{s,t}$ denote the fitted values from our model. We define our counterfactual as

$$\tilde{y}_{s,t} = \hat{y}_{s,t} - \hat{\beta} TPU_{s,t} + \hat{\beta}\overline{TPU}_s$$

for $t \geq First\ quarter, 2016$. Then, we calculate the amount of discouraged FDI (in US dollars) due to higher TPU as

[29] See Box 4 in Banco de Mexico's Report of Regional Economies Oct-Dec 2016.

$$\sum_{s} \sum_{t=First\ quarter,2016}^{Fourth\ quarter,2018} (\tilde{y}_{s,t} - \hat{y}_{s,t}) GDP_t.$$

Using the results from our split sample regression (columns 2 and 3 in Table 1), our counterfactual yields a total of 15.5 billion dollars of ¨lower FDI¨ during the period.[30] The distribution of this loss across years is uneven, with 62 percent of the estimated loss being attributed to the discouraged FDI for 2018. The five most affected entities, excluding Mexico City, were Nuevo León, Jalisco, Estado de México, Puebla, and Baja California which are states that command a large share of Mexico's manufacturing capability.[31] Thus, we estimate that for the period that extends from the first quarter of 2016 to the last quarter of 2018, FDI was 15.5 billion dollars below what would have been observed in the absence of the increase in trade policy uncertainty.[32]

To put this number into perspective, consider that Audi invested 1.3 billion dollars in its newest plant in Mexico, that total foreign direct investment in the Mexican automotive sector in 2015 was 5.8 billion dollars, or that total FDI flows into Mexico between the first quarter of 2016 and the first quarter of 2017 amounted to 35 billion dollars. Thus, considering that no *actual* changes in trade policy were observed during the period under consideration, the estimated "missing FDI" represents an economically meaningful negative impact of increased trade policy uncertainty on foreign direct investment. This result is similar to those in Handley and Limao [2017] who find that trade policy uncertainty has a negative effect on domestic investment as firms are more reticent to invest in technology upgrading.

While our results show that uncertainty has an adverse effect on foreign direct investment, in the appendix we show that increased uncertainty can lead to expansionary effects for other variables. In particular, we study export participation decisions and argue that, from the real-

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[30] This loss is concentrated in export oriented states, given that we assume $\beta = 0$ for non-export oriented states since our split sample regression implies that β is not statistically different from zero for that group of states.
[31] We exclude Mexico City because it is an outlier in terms of both participation in FDI inflows and Google searches generated.
[32] If instead of using our estimates for β from the split sample regression, we assigned to all states the same estimated β from our pooled regression, we would have calculated a total of 15.2 billion dollars in discouraged FDI.

options perspective, higher uncertainty can lead to increased market entry, for marginal export entrants, due to an expectation of future increases in market entry costs and the fact that market entry is an easily reversible decision.[33] We present evidence regarding export probabilities for 6-digit NAICS products and show that for some products, an increase in TPU leads to an increase in export probabilities when the destination market is the United States and to no change in export probabilities for all other destinations, consistent with the theoretical framework that was outlined.[34] These results, as our results for foreign direct investment, lend support to the real-options perspective of decision making under uncertainty.

4. Final remarks

This paper contributes to the understanding of the effects that trade policy uncertainty can have on the decisions of economic agents. We have used the case of Mexico, which has recently faced an important jump in TPU due to the increased prevalence of a protectionist position in the U.S., Mexico's main trading partner. We constructed a measure of TPU for the Mexican economy based on data from Google Trends and used it to quantify the impact that an increase in trade policy uncertainty has had on foreign direct investment. Our main result indicates that the increase in trade policy uncertainty that the Mexican economy has experienced since the second half of 2016 had a negative impact on flows of foreign direct investment, particularly in export-oriented states. Our results confirm that even in the absence of actual changes in trade policy, uncertainty about these policies can have an important impact on the decisions of economic agents.

The enactment of NAFTA in 1994 represented a new institutional arrangement designed to promote trade and investment flows among its members. To this end, a cornerstone of the agreement has been to eliminate barriers and to create an environment that promoted regional

[33] The decision problem under uncertainty that we have in mind regarding market entry is outlined in detail in the appendix.
[34] The result applies to what we deem "sometimes exported" products, which in the context of our empirical analysis correspond to marginal export decisions.

integration. In this sense, our results suggest that uncertainty can be an important barrier to integration through investment flows.

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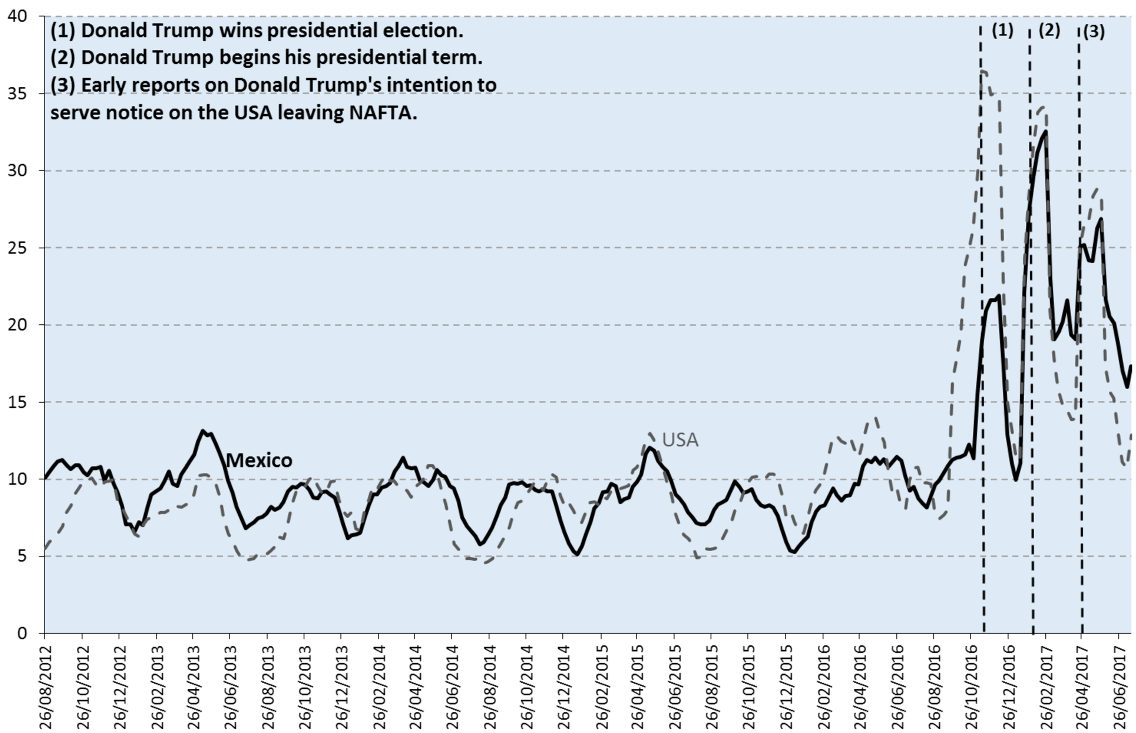
6. Figures and Tables

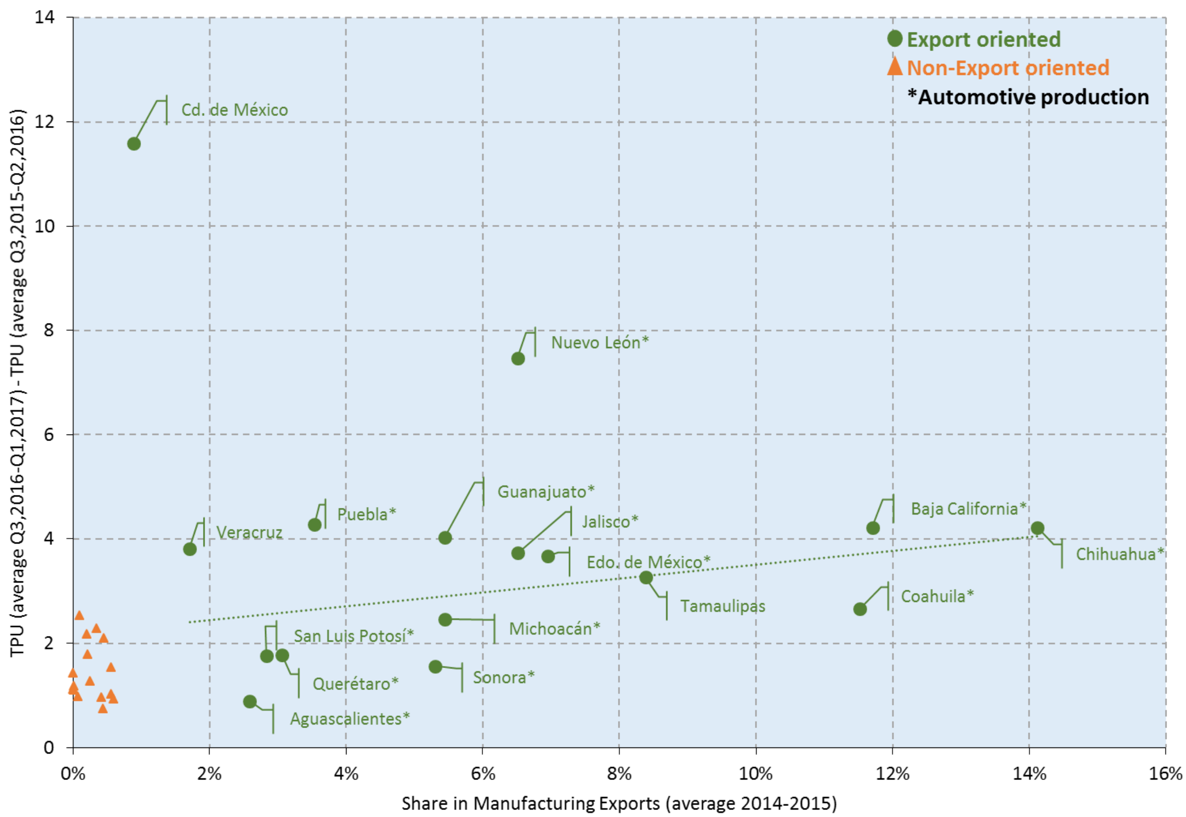
Figure 1. Trade Policy Uncertainty Index based on Google Trends data



Source: Own calculations with data from Google Trends. The black solid line corresponds to the TPU index for Mexico, while the grey dashed lined corresponds to the index for the US. The TPU index for Mexico is constructed as a weighted average of the terms "NAFTA", "TLCAN", "renegotiation", "NAFTA renegotiation", "tariffs", "NAFTA Trump", "TLCAN Trump Mexico", "free trade", and "what is NAFTA". We construct the TPU index for US in an analogous fashion, except that the search terms included in the index are "NAFTA", "TLCAN", "tariff", "NAFTA Trump", "what is NAFTA", "NAFTA pros and cons", "NAFTA news", "NAFTA renegotiation", and "free trade". Each data series from Google Trends is an index between 0 and 100, where 100 corresponds to the date of maximum popularity for the term within the reference period and all other values are relative to this date of maximum popularity. That is, a date at which the index takes the value of, for example, 50 corresponds to a date in which the search term was half as popular as on the date of maximum popularity. Values of zero for the index correspond to dates on which the popularity of the search terms is less than 1% relative to the value of 100. Notice that the time series reported in this figure never take on the value of 100. This is the result of two types of averaging: first, our weekly index is the weighted average of indices that may take on the value of 100 at different dates; second, in this figure we are reporting a 6-week moving average of our weekly index.

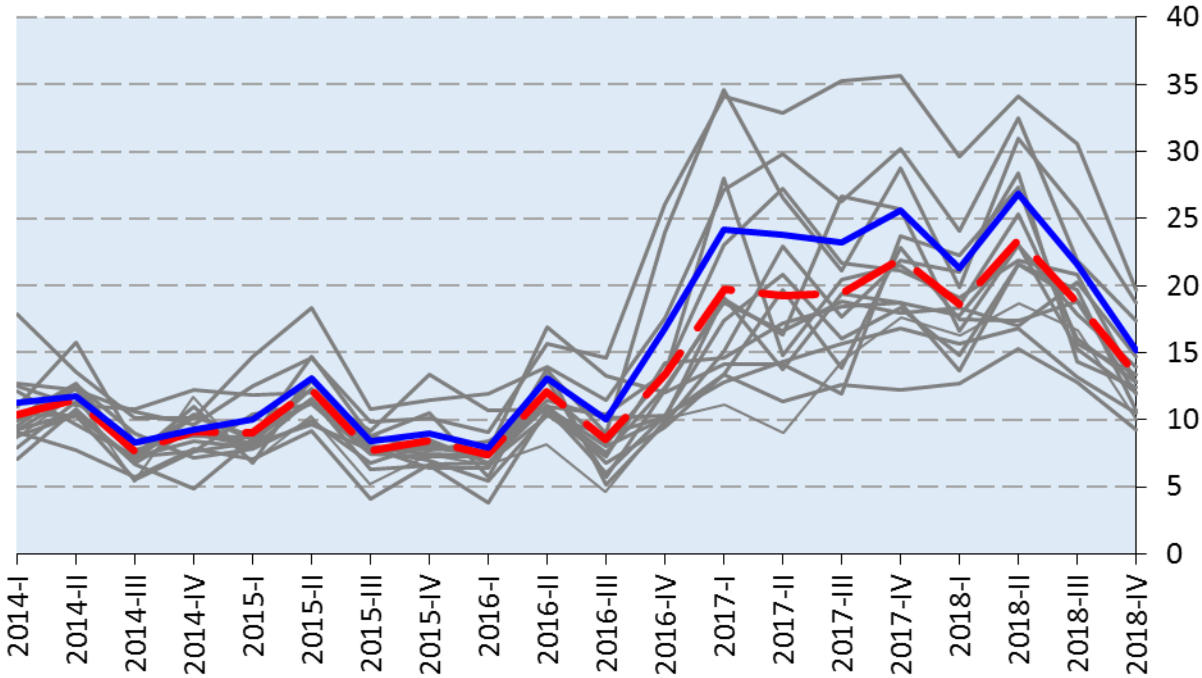
Figure 2. Regional variation in TPU across states in Mexico

relative to their degree of export orientation



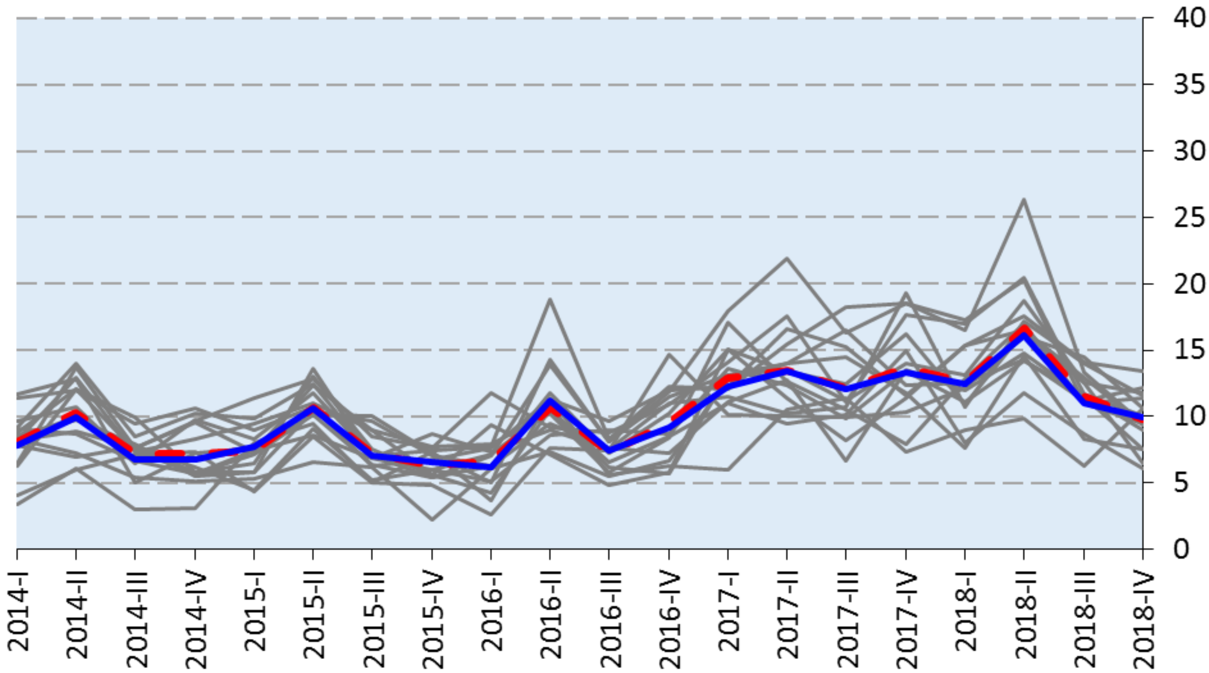
Source: The change in TPU is calculated as the differences between average TPU for 2016Q3-2017Q1 and the average TPU for 2015Q3-2016Q2 (see Figure 1 and section 2 for details regarding the construction of our TPU index). Exports correspond to state-level manufacturing exports. The source for the information on state-level exports is INEGI (https://www.inegi.org.mx). The average for each state's share in manufacturing exports is computed for the period 2014-2015. Export-oriented states are defined as states whose share in manufacturing exports is above the median value across all states. The trend line that is included in the graph is only for export-oriented states, excluding Mexico City. States with automotive production correspond to the geographic distribution of production plants reported by PwC Mexico in 2014 (https://www.pwc.de/de/internationale-maerkte/assets/doing-business-mexico-automotive.pdf).

Figure 3. Trade Policy Uncertainty Index based on Google Trends data: Export Oriented States



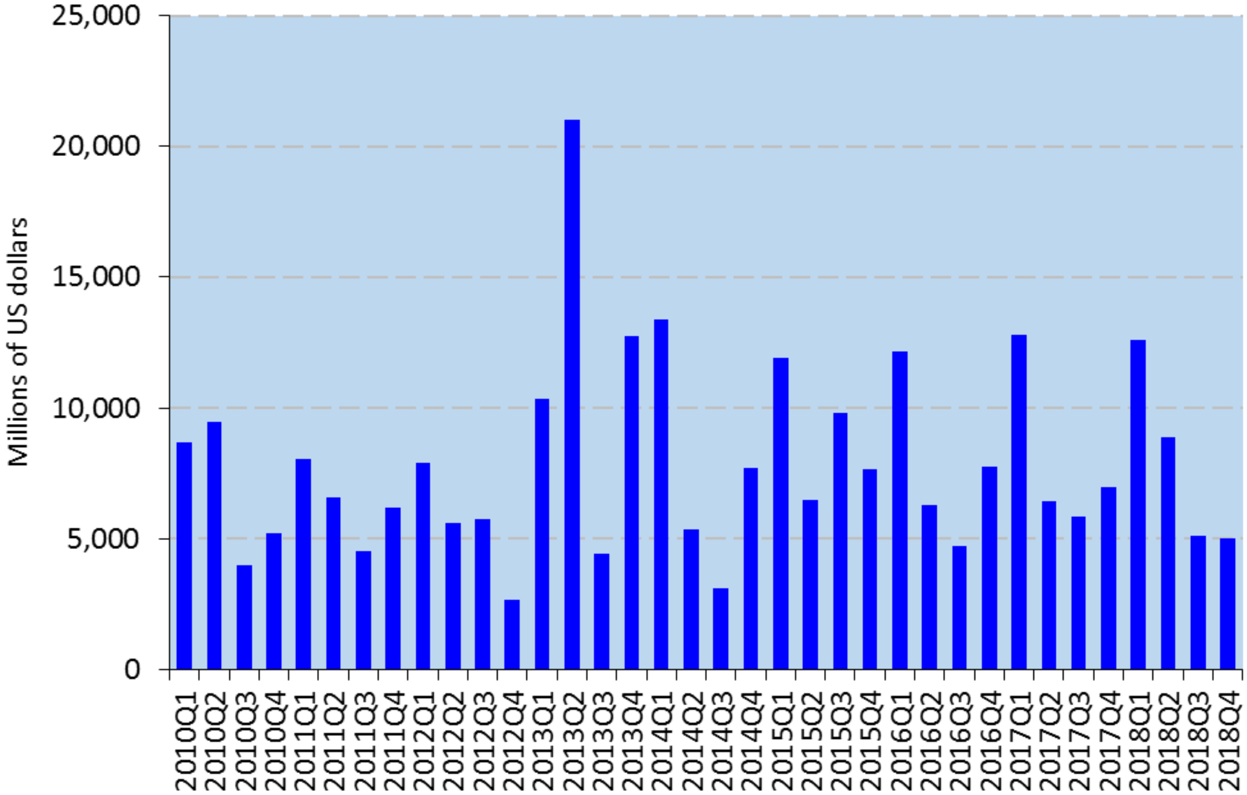
Source: Own calculations with data from Google Trends. The grey lines correspond to the TPU index calculated at the state level for the sixteen states classified as export oriented (see Figure 2). The blue solid line corresponds to the weighted average of the state-level TPU indices, using as weights each state's average participation in total GDP produced by this group of states during the period 2013-2017. The red dashed line corresponds to the simple of average of state-level TPU indices. The state level index at the quarterly frequency is the result of averaging the index constructed at the weekly level for those weeks that belong to each quarter.

Figure 4. Trade Policy Uncertainty Index based on Google Trends data: Non-Export Oriented States



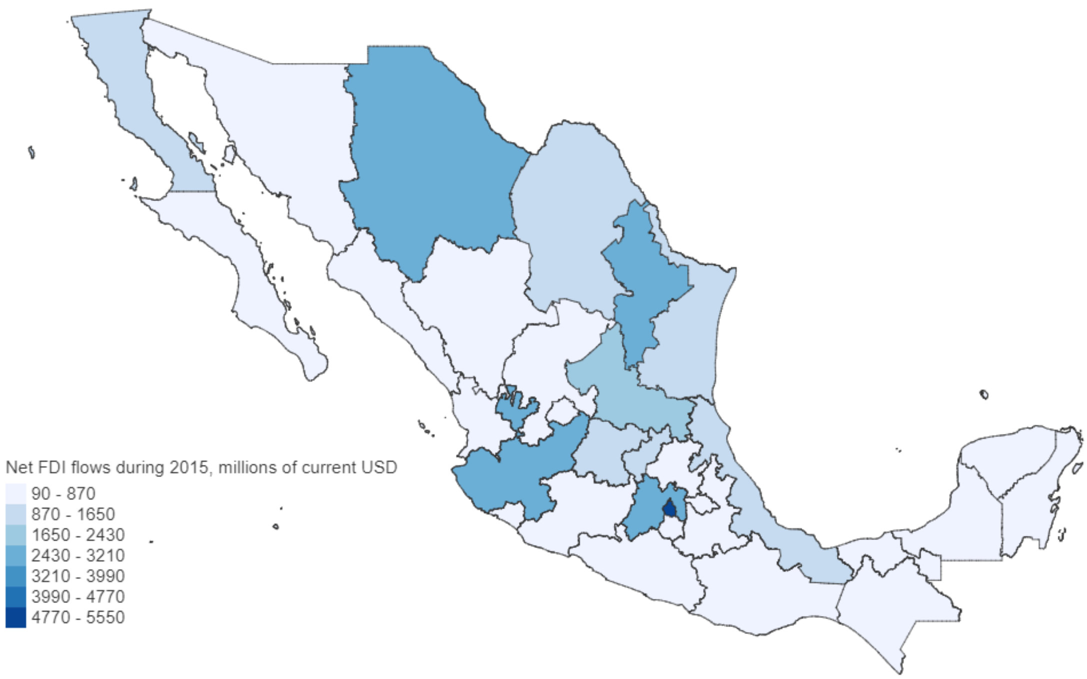
Source: Own calculations with data from Google Trends. The grey lines correspond to the TPU index calculated at the state level for the sixteen states classified as non-export oriented (see Figure 2). The blue solid line corresponds to the weighted average of the state-level TPU indices, using as weights each state's average participation in total GDP produced by this group of states during the period 2013-2017. The red dashed line corresponds to the simple of average of state-level TPU indices. The state level index at the quarterly frequency is the result of averaging the index constructed at the weekly level for those weeks that belong to each quarter.

Figure 5. Evolution of flows of foreign direct investment into Mexico, 2010-2018



Source: Own calculations based on data from Secretaría de Economía (https://www.gob.mx/se/).

Figure 6. Distribution of FDI flows into Mexico across states, 2015



Source: Own calculations based on data from Secretaría de Economía (https://www.gob.mx/se/). The data is reported at the state-level in millions of US dollars at a quarterly frequency

Table 1. Effects of TPU on FDI

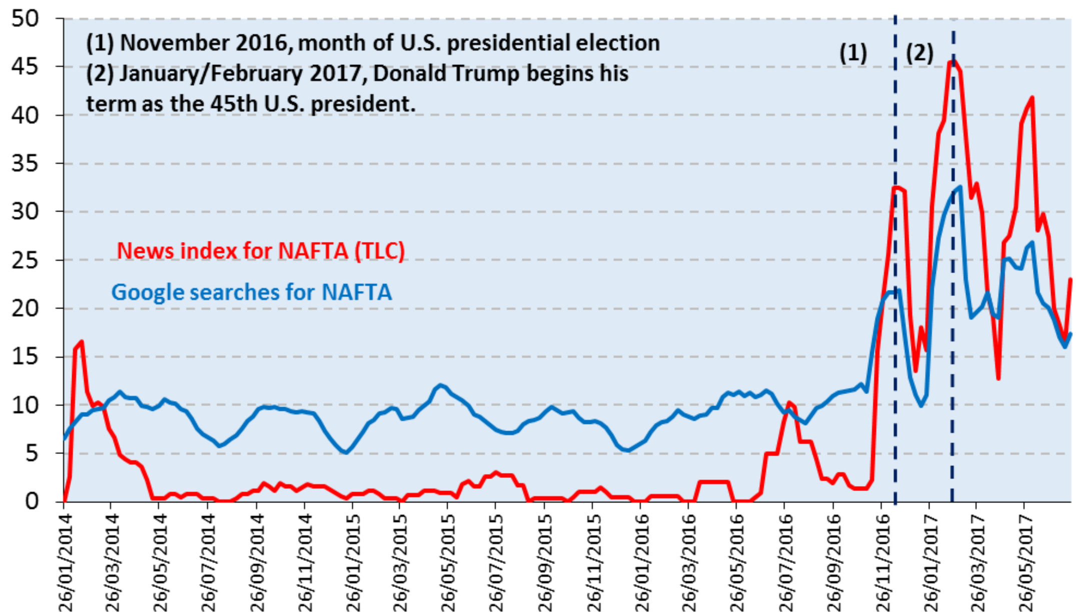
FDI as % of GDP	Pooled	Export Oriented	Non-Export Oriented
TPU	-0.000008*	-0.000012*	0.000002
	(0.000005)	(0.000007)	(0.000003)
TPU (standardized coeff.)	-0.114	-0.162	0.088
Homicide Rate	-0.000001	0.000003	-0.000001
	(0.000002)	(0.000008)	(0.000001)
State FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes
Observations	640	320	320
Adjusted R^2	0.71	0.73	0.53

Notes: This table presents the results of the estimation of equation (1). The dependent variable is a measure of state-level foreign direct investment as a share of national GDP. In this estimation, TPU corresponds to the four-quarter moving average of the quarterly TPU index. The homicide rate corresponds to the number of homicides per 100,000 persons. The sample period extends from the first quarter of 2014 to the last quarter of 2018. Export-oriented states are defined as states whose share in manufacturing exports is above the median value across all states. Standard errors, in parentheses, have been clustered at the state level. Significance codes: * *p<0.10*, ** *p<0.05*, *** *p<0.01*.

7. Appendix

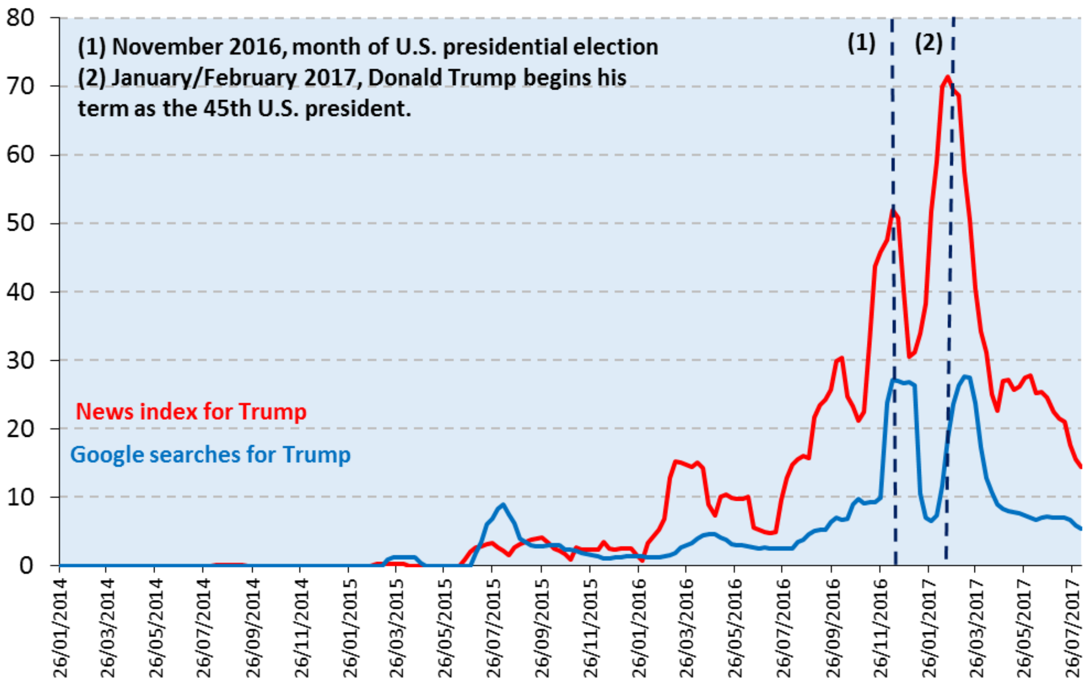
7.1 Appendix to Section 2

Figure A1. Popularity of the Word NAFTA in Google Searches and News Based Mentions



Notes: This graph presents a 6-week moving average for the Google Trends data related to the search-term "NAFTA", which is one of the components of the TPU index reported in Figure 1 of the main text. Together with this time-series we present the time-series for news-based mentions of the term "TLC" (i.e. NAFTA) in the principal newspapers of national circulation in Mexico. This series is based on the relative frequency with which the term "TLC" appears in the covers of the newspapers under consideration. Each data point is constructed based on between 6 and 12 newspaper cover depending on how many of the newspapers under consideration are published on a given day. The mode is 10 newspapers per data point. Each newspaper cover is stripped from what the big data literature calls "stop words" which include articles and prepositions, and generally the most commonly used words in the language. From the remaining text we count the number of times the term "TLC" appears relative to the total number of words used. The time series derived from this process is normalized against the day with the maximum frequency to obtain an index between 0 and 100 in order to make this series more comparable to the way Google Trends reports its data. Notice that both time series have a qualitatively similar behavior over the sample period. This is suggestive of the fact that our choice to construct the TPU index based on Google Trends data rather than news-based mentions as in Baker et al. [2016] may not necessarily be a drawback of our index, at least as compared to a news-based proxy for trade policy uncertainty.

Figure A2. Popularity of the Word Trump in Google Searches and News Based Mentions



Notes: This graph presents a 6-week moving average for the Google Trends data related to the search-term "Trump". Together with this time-series we present the time-series for news-based mentions of the term "Trump" in the principal newspapers of national circulation in Mexico. This series is based on the relative frequency with which the term "Trump" appears in the covers of the newspapers under consideration. Each data point is constructed based on between 6 and 12 newspaper cover depending on how many of the newspapers under consideration are published on a given day. The mode is 10 newspapers per data point. Each newspaper cover is stripped from what the big data literature calls "stop words" which include articles and prepositions, and generally the most commonly used words in the language. From the remaining text we count the number of times the term "Trump" appears relative to the total number of words used. The time series derived from this process is normalized against the day with the maximum frequency to obtain an index between 0 and 100 in order to make this series more comparable to the way Google Trends reports its data.

7.2 Appendix B: Uncertainty, Option Values and Export Participation

While not the main focus of this paper, in this section we argue that uncertainty may affect export activity via option values that affect the market entry decisions of firms. We provide some empirical evidence in support of this mechanism.

For the case of export market participation decisions, we conceptualize the underlying decision problem faced by firms as some variant of the problem studied by Das et al. [2007], which itself is a partial equilibrium, dynamic version of the export market participation problem studied in Melitz [2003]. A key feature of this decision problem is that firms face both tariff and non-tariff barriers to exporting. The structure of non-tariff barriers is particularly important as they induce rich dynamics into the export supply decision of firms. Das et al. argue that firm-level dynamics observed in the data suggest that firms face both per-period fixed costs to exporting and export market entry costs that need to be paid every time they commence a new export spell. That is, every time a firm wants to venture into the foreign market, after not having exported recently, it will have to pay a series of fixed costs that it only pays on that initial period and thereafter it only pays the fixed costs associated with maintaining its export presence. If, as previously argued, the most important source of trade policy uncertainty faced by firms in Mexico is regarding the non-tariff barriers to trade (i.e. the fixed costs associated with market entry and maintaining an export presence), then increased uncertainty may lead to a higher probability of exporting. To see why, note that: (a) exporting is an easily reversible decision since an exporting firm faces no barriers in the reversal of this decision (i.e. there are no obstacles to stop exporting), and (b) by exporting today, even if this entails a negative profit in the current period, firms gain the option tomorrow to pay the low fixed costs associated with maintaining their export presence rather than have to pay the possibly larger export entry costs required to initiate an exporting spell.

To make this line of reasoning more precise, we present a heuristic derivation of this result regarding the effect that trade policy uncertainty has on the extensive margin of market entry in international trade in the context of a setup that draws heavily on the dynamic export supply model outlined in Das et al. [2007]. In such a model of export participation and firm heterogeneity, firm i will decide to export if and only if the value of exporting exceeds the fixed costs associated with export activity:

$$\pi(\varphi_{it}) + \beta\delta E_t\left[V_{i,t+1}^1 - V_{i,t+1}^0\right] - F_{it} \geq 0,$$

where $\pi(\varphi_{it})$ are the variable profits from exporting for a firm with current productivity φ_{it}, $V_{i,t+1}^1$ is firm i's continuation value at time *t+1* if at time t it decides to export and $V_{i,t+1}^0$ is firm i's continuation value at time *t+1* if at t it decides not to export, F_{it} are the fixed costs of exporting for firm i at time t, β is the time discount factor, and δ is the firm's exogenous survival probability.

Under the standard assumption that firms face CES demands (see, for example, Melitz and Redding [2014]), the above condition can be written as a cutoff rule:

$$X_{it} = 1 \quad iff \quad \varphi_{it} \geq B_t(F_{it} - O_{it})^{\frac{1}{\sigma-1}},$$

Where X_{it} is an indicator function equal to 1 if firm i decides to export at time t, B is a function of parameters and aggregate variables that all firms take as given and which represents the "strength of demand" at the destination market[35], $\sigma > 1$ is the elasticity of the CES demands faced by firms, and $O_{it} \coloneqq E_t\left[V_{i,t+1}^1 - V_{i,t+1}^0\right]$ is the firm's *option value* for becoming an exporter at time t (i.e. the expected value perceived by the firm of arriving to the next period as an exporter rather than as a non-exporter).

Following the discussion in Das et al., we specify the fixed costs of exporting as

$$F_{it} = F + \left(1 - X_{i,t-1}\right)F_s,$$

Where F denote per-period fixed costs of exporting that have to be paid every time firm i decides to serve the foreign market and F_s are sunk entry costs that firm i has to incur in each time it starts a new exporting spell (i.e. if firm i exported at time *t-1* and it wants to export again at time t, it does not have to pay F_s again).

[35] The "strength of demand" at the destination market typically depends on aggregate spending and the ideal price index at the destination. See Melitz and Redding [2014] for details.

Notice that the presence of the sunk cost F_s induces dynamics in the export supply problem, as by having exported today the firm can decide to maintain its export status tomorrow at a lower cost (i.e. by only paying F). That is, in the absence of these sunk costs there would be no option value for becoming an exporter and the dynamics of export supply would be characterized by a series of static profit maximization problems in which the firm would only assess, period by period, whether the variable profits from exporting are sufficient to cover the fixed costs of exporting.

Now, considering the export supply problem addressed in the main text, since there are two foreign destinations under consideration and since, under standard assumptions (see Melitz and Redding [2014]) market entry decisions are separable across markets we have that

$$X_{it}{}^{d} = 1 \quad iff \quad \varphi_{it} \geq B_t{}^{d}\left(F_{it}{}^{d} - O_{it}{}^{d}\right)^{\frac{1}{\sigma-1}},$$

for $d \in \{USA, ROW\}$. That is, there are two separate cutoff rules characterizing export participation in each destination market and firms decide separately about their participation in each market.

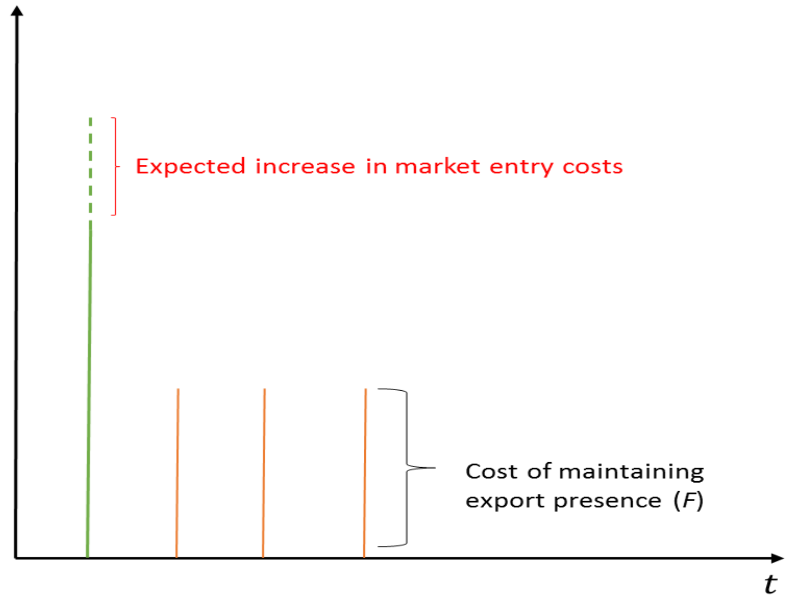
In the main text it was argued that given the nature of NAFTA and the low and certain MFN tariffs faced by Mexican exporters to the US, trade policy uncertainty would mostly manifest itself as uncertainty regarding the general conditions for access to the US market that Mexican exporters could potentially face. That is, we have in mind a scenario in which trade policy uncertainty is mostly uncertainty about the future values of F^{USA} and F_s^{USA}, mainly regarding the sunk cost since this to a large extent reflects, among other things, the costs of setting up supply and distribution networks and of learning how to comply with administrative procedures.[36] A simplified scenario in which only the sunk market entry cost is foreseen as possibly increasing is depicted in Figure B1, but the general point goes through if the fixed cost F^{USA} are also expected to increase. Notice, in particular, that in the scenario we have in mind there is only downside risk: firms assign positive probability to the case in

[36] For example, in those cases in which rules of origin are a requirement for exporting tariff free under NAFTA, it is up to the exporter to prove compliance with the regional content requirements.

which market entry costs increase, but no probability to the case in which market entry costs decrease.

Now, consider the impact of trade policy uncertainty on export participation in this setting. For the case of destinations other than the USA (i.e. the rest of the world), market entry costs are unchanged relative to the initial situation and trade policy uncertainty may only indirectly affect export participation decisions through a possible effect on the "strength of demand" B^{ROW}. However, we assume that for the situation under consideration these effects are second order and, therefore, trade policy uncertainty has no impact on export participation decisions of Mexican exporters in destinations that are not the USA. However, in the US the expectation that market entry costs, F_s, will increase implies that, everything else equal, the option value to becoming an exporter today is larger than in the future (i.e. $O_{it} > O_{is}$ for $s > t$): by exporting today at a low entry cost exporters acquire the option of retaining their export status tomorrow at a low cost rather than initiating an export spell once entry costs F_s have increased. Thus, the right-hand side of the export participation decision for the US market is relaxed, which leads to the entry of marginal exporters.

Figure B1. Uncertainty about market entry costs



$$F_{it} = F + (1 - X_{it-1})F_s$$

This positive effect of uncertainty regarding export market entry costs on export participation decisions is akin to the Oi-Hartman-Abel effect whereby, if firms can expand to exploit good outcomes and contract to insure against bad outcomes, they may be risk loving (see Bloom [2014]). Mexican firms may anticipate that commencing an export spell will entail larger export entry costs in the case of a dissolution of NAFTA or a one-sided renegotiation of the treaty due to, among other factors, greater costs to establish a contact network in the U.S. due to, perhaps, a less efficient matching process with U.S. firms. Since the fixed costs associated with exporting are larger relative to revenues for marginal export participants, increased uncertainty regarding export entry costs may be particularly important for marginal export decisions. Thus, it is possible that increased trade policy uncertainty that takes the form of uncertainty regarding future market entry costs, increases the probability of exporting today for marginal export participants as this represents an option to be exercised at a later date to maintain their export presence without having to pay the possibly higher fixed costs for initiating an export spell.

In the remainder of this section we empirically investigate the effect of increased trade policy uncertainty on export participation decisions. As in Handley [2014], we approximate firm-level participation decisions by estimating export probabilities for HS-6 digit products at a monthly frequency. The export data that we employ is aggregated from customs data containing the universe of Mexican exports.[37] The data used for estimation comprises the period January 2012 to May of 2017 and is constructed to distinguish between two export-destination markets: the US and the rest of the world (ROW).[38]

During our reference period, a total of 4,928 unique HS 6-digit products were exported by Mexico at some point. Thus, we take this to be the available "menu" of products that Mexico can export.[39] For some products, the total value of exports at a given date is extremely low during our sample period. We recode the data so that monthly export flows with a value of under 500 USD are reclassified as zeros.[40] This reclassification affects a relatively small number of observations, but will be useful in what follows.[41]

We partition the universe of products available in Mexico for exporting into three groups: 1. *Never exported*: these correspond to products that have an export value of zero for both export destinations for the entire reference period;[42] 2. *Always exported*: these correspond to products that record a positive export value for both destinations for the entire sample period,

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[37] Customs data provides information regarding the product classification and destination of firm-level exports. We aggregate this raw data to the product-destination level using the HS 6-digit classification to define product categories and we define two foreign markets served by Mexican exporters: the United States and the rest of the world (ROW). Since the US is Mexico's top trading partner, commanding roughly 80 percent of total Mexican exports, and that the increase in trade policy uncertainty during our reference period mainly concerns the future of this bilateral relation, we believe that this binary classification of export destinations is adequate for the purposes of our exercise.

[38] This exercise was not updated beyond May 2017 as the effect of uncertainty on export activity was not the main focus of this paper and Trump's trade war, which involved several key trading partners including Mexico, introduced additional complications to empirically analyze the effect of uncertainty on export activity.

[39] Technically, our product menu will consist of 4,924 products since four of the 4,928 products were recorded with a code that did not correspond to any of the codes in the HS classification.

[40] For example, if at time t the dollar value of exports of product j totals \$100, then we recode this trade flow as \$0 exported for product j at time t.

[41] This kind of truncation of the data is common in the international trade literature, as many data sets do not record transactions under \$2500. Censoring at the 350 USD value does not alter our results in any noticeable way.

[42] "Never exported" products are obviously not products that Mexico has not exported, but rather consist of products where the total dollar value of exports is extremely low and were reclassified as zeros.

and 3. *Sometimes exported*: these correspond to products that exhibit some variation, either across time or across destinations, in terms of their export status. Table B1 presents some basic summary statistics for our export data based on this partition of products and distinguishing between export destinations.[43] Table B2 provides summary statistics disaggregated by the broad sector of economic activity to which products belong to. It is readily seen from these two tables that gravity forces play a strong role in shaping the export participation decisions of Mexican exporters: there are more products that are always exported and less products that are never exported to the US relative to ROW and for nearly all sectors of economic activity the share of never exported products is lower and the share of always exported products is higher in the US as compared with other export destinations. Additionally, the number of products that are uniquely sold in one export market is higher in the US than in the rest of the world. This shows the importance of the bilateral US-Mexico relationship for the Mexican economy.

Since the product categories "never exported" and "always exported" contain no time-series or cross-sectional variation that we can exploit for identification, our benchmark estimates will rely on the subsample of "sometimes exported" products. This subsample contains a total of 3,412 HS 6-digit products covering all sectors of economics activity.[44] An important point, as it relates to our earlier discussion regarding the expected effects of trade policy uncertainty on export participation, is that the subsample used for estimation corresponds to Mexican products that are marginally exported. As can be seen in Table B3, the class of products "always exported" —that could be considered as the set of core products in Mexican exports— commands nearly the entire share of export value. That is, this product category commands roughly 92 percent of the total monthly value exported during the sample period. By definition, the export status of these products has not been affected by changes in TPU during our sample period.[45] However, given our earlier discussion we could expect that

[43] All tables and figures are reported in subsection 7.2.1.

[44] The products in our sample include products from the following sectors: Animal & Animal products, Vegetable products, Foodstuffs, Mineral products, Chemicals & Allied industries, Plastics/Rubbers, Raw hides, skins, leather, & furs, Wood & Wood products, Textiles, Footwear/Headgear, Stone/Glass, Metals, Machinery/Electrical, Transportation, and Miscellaneous.

[45] Notice, however, that this statement does not preclude the possibility that trade policy uncertainty has affected the intensive margin of trade associated with these products or the underlying extensive margin of firm

greater trade policy uncertainty may increase the probability of exporting some products at the margin (i.e. "sometimes exported" products).

In our analysis of the impact of trade policy uncertainty on foreign direct investment we exploited the fact that both FDI and our TPU index varied across states and time. However, in this section where we analyze export status at the product level our outcome of interest varies across time and products, but not by states. Given that our TPU index is constructed at the state level and that a similarly constructed index is not available at the product level, here we construct a proxy for trade policy uncertainty at the product level by apportioning state-level TPU according to the state's share in total employment for that product.[46] This way of constructing our measure of exposure at the product level is similar to the methodology suggested in Autor et al. [2013], who construct measures of exposure to Chinese import penetration at the regional level by apportioning import penetration at the sector level according to the region's employment share in the sector. Thus, we define our measure of each product's exposure to trade policy uncertainty, $ETPU$, as

$$ETPU_{jt} = \sum_{i} \frac{E_{ij}}{E_j} TPU_{it},$$

where TPU_{it} is trade policy uncertainty in state i, E_{ij} is the employment that can be attributed to the production of product j located in state i, and E_j is total national employment that can be attributed to the production of product j.[47] The intuition behind our ETPU measure is that

participation. That is, an "always exported" product may maintain its export status continually even when the associated export volumes are changing and/or the number of firms underlying the export supply of a given product is changing. In this sense our approach is narrow and has nothing to say regarding the impact of trade policy uncertainty on these other margins of adjustment of exporting activity.

[46] We also considered using value added and gross production to apportion state-level TPU. However, state-level employment is available at a much more disaggregated sectoral classification than what is available for either of the former measures at the state-level. Thus, we construct our ETPU measure with employment weights since in this case we are able to better match HS 6-digit products with the NAICS sectors for which employment is reported.

[47] Employment data for 2007 NAICS 6-digit industries are obtained from the 2009 Economic Census published by INEGI (http://www.inegi.org.mx/). We use correspondence tables between 2012 NAICS 6-digit industries and HS 8-digit products. As 2012 NAICS 6-digit industries describe industrial activity to a greater degree of specificity than do the 2007 classification employed by the Economic Census, there is a slight mismatch when merging the data based on the correspondence tables previously mentioned. Specifically, we can only directly assign TPU by 2007 NAICS 6-digit industry to approximately 92% of the 3,252 HS 6-digit products exported

products whose production is more concentrated in states where TPU is high are assumed to be more heavily exposed to trade policy uncertainty. That is, we think of a product whose production is highly concentrated in states with high TPU as being very exposed in comparison to a product whose production is concentrated in states with low TPU. Table B4 reports the share of products in each sector of economic activity that have an exposure to trade policy uncertainty above the median value across all products.

To estimate the effect of exposure to trade policy uncertainty on export participation decisions, we consider the following linear probability model

$$T_{jdt} = \beta \overline{ETPU}_{j,t-1} + \delta_{jd} + \delta_{dt} + \delta_m + \varepsilon_{jdt}, \qquad (2)$$

where T_{jdt} is an indicator for whether product j was exported to destination d at time t (using monthly data). The coefficient of interest is β and $\overline{ETPU}_{j,t-1}$ is the average of $ETPU_j$ over *t-3*, *t-2*, and *t-1*. We use a three- month moving average of $ETPU_j$ since at the monthly frequency trade policy uncertainty displays enormous variability. Our econometric specification also includes a product-destination fixed effect (δ_{jd}) that controls for time-invariant reasons for why some products may be more likely to be exported to one destination than another such as, for example, comparative advantage and/or integration in value chains; a destination-time fixed effect (δ_{dt}) that controls for factors affecting the probability of exporting to a destination for all products such as exchange rate fluctuations vis-à-vis export market d or changes in the demand for imports in the foreign market; a fixed effect for the month in which exports took place (δ_m) to control for seasonal effects. Analogous to the case of foreign direct investment, the identification of the coefficient of interest relies on exploiting both time-series and cross-sectional variation in the data.

Before presenting our baseline results for the estimated effect of exposure to trade policy uncertainty on export probabilities, we present two other results from our estimation that shed

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intermittently. Our strategy to retain the remaining 8% is to successively impute the average value of TPU by 5, 4, 3, and 2-digit 2007 NAICS sector to this set of products.

light on the manner in which the Mexican economy is engaged with the rest of the world through exports. Additionally, these results also serve as a way of checking whether the results from our econometric model reflect our prior knowledge regarding the behavior of Mexican exports. First, let $\hat{p}_{jdt}$ denote a fitted value from our estimation. Define

$$\hat{p}_{dt} = \frac{1}{N}\sum_{j=1}^{N} \hat{p}_{jdt}$$

as the average export probability of exporting to destination d at time t. Figure B1 presents the time series for the average probability of exporting to the U.S. and to the rest of the world, respectively. It is clear that for Mexican exporters the average probability of exporting to the U.S. is always larger than that of exporting to other export destinations. This is what one would expect given the large size of the US market and the lower trade costs faced by Mexican exporters serving that market relative to the rest of the world.

The next exercise that we consider relates to the time-invariant component of export probabilities. We define

$$\hat{\gamma}_j = \hat{\delta}_{j,USA} - \hat{\delta}_{j,ROW}$$

as the "export premium" of product j in the US market relative to the rest of the world. This "U.S. export premium" captures issues such as differences across markets in terms of integration through value chains and production sharing arrangements, differences in the comparative advantages of Mexico relative to the foreign destinations that it serves, differences in language and institutions that may facilitate or inhibit trade, among other things. Figure B2 and Table B5 present these export premia by product ordered from highest to lowest. The average export premium is positive, reflecting that on average it is more likely that any given product is exported to the U.S. than to other foreign destinations. However, it is also interesting to note that the export premium is negative for several products. That is, there exist certain products such that if market conditions are the same across destinations (i.e. $\delta_{USA,t} = \delta_{ROW,t}$), then exporting to the rest of the world is more likely than exporting to the US. This, in part, reflects the fact that comparative advantage is defined relative to a trading partner. Thus, while Mexico may enjoy a comparative advantage in certain products vis-à-vis the US, it may enjoy a comparative advantage in other products vis-à-vis the rest of the world. For example, our estimation indicates that the average export premium in the chemical and allied industries sector is negative and thus suggests that in this industry Mexican exporters are, other things equal, more likely to export their products to the rest of the world than they are to the US.

Finally, our benchmark estimates for the effects of exposure to trade policy uncertainty on the probability of exporting are reported in column 1 of Table B6. We find that an increase in TPU has a positive and statistically significant effect on the probability of exporting. That is, we find evidence that an increase in trade policy uncertainty has a positive effect on export participation decisions. Because the sample used for estimation only includes the products classified as "sometimes exported" that command only a small share of the total value of Mexican exports, our results lend support to our initial hypothesis that increased uncertainty can have a positive effect on marginal export-entry decisions. This contrasts with the result of Handley and Limao [2017], who find that trade policy uncertainty has a negative effect on trade. However, as noted in a previous section, the nature of trade policy uncertainty under consideration here is arguably different from that studied by those authors, and we focus on trade policy uncertainty more broadly, not only on uncertainty about tariffs. [48] Thus, we see our results as complementary to theirs and as an additional contribution that furthers our understanding regarding the ways in which trade policy uncertainty, and uncertainty more generally, affects the decisions of economic agents.

[48] These authors consider a setting in which firms face known and constant export market entry costs and face uncertainty regarding variable trade costs (i.e. tariffs). In that case uncertainty about variable trade costs has a negative effect on the expected discounted stream of profits that justify paying the upfront costs for export market entry. Thus, in Handley and Limao [2017] trade policy uncertainty has a negative effect on export participation decisions. As noted earlier, in our case we consider tariff uncertainty as second order when compared to the uncertainty that firms face regarding future market entry costs into the US market. Thus, since there is no expectation that these costs may be lower in the future and all the risk is concentrated on these costs being higher, firms have an incentive to enter the market early and acquire the option of maintaining their export status without having to pay higher market entry costs.

As a robustness check on the estimates presented in Table B6, we consider the following logit specification of our benchmark specification

$$p_{jdt} = F\left(\delta_j + \delta_d + \delta_t + \delta_m + \beta \overline{ETPU}_{j,t-1}\right),$$

and an estimation of our benchmark linear probability model on the full sample of products. The results of these two estimations are presented in Tables B7 and B8. In both instances the estimated effect of greater exposure to trade policy uncertainty on export probabilities is positive and statistically significant. In the case of the estimation of the linear probability model described by equation (2) on the full sample of HS 6-digit products exported by Mexico, the estimated effect of ETPU on export probabilities is smaller than the effect reported in Table B6. However, this is to be expected given that the products that are re-introduced into the sample are products that by definition have not yet modified their export status in response to the increase in trade policy uncertainty.

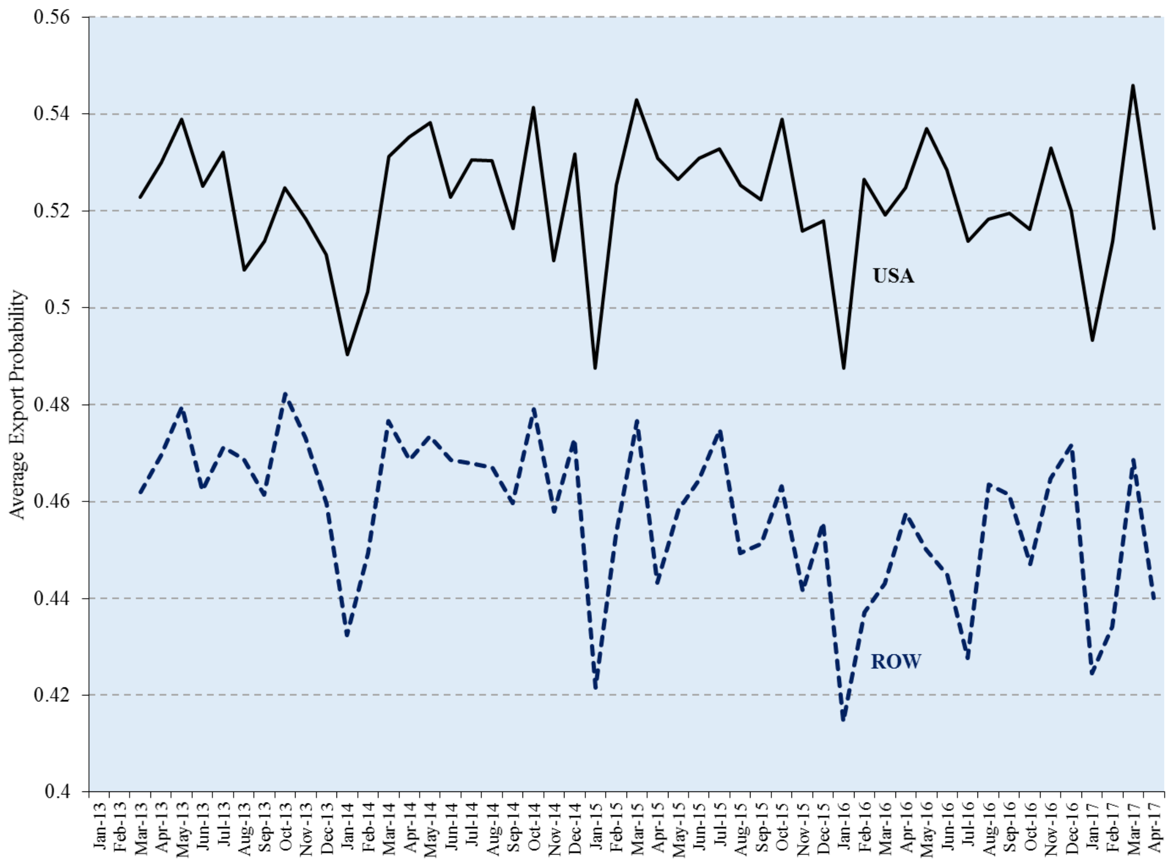
The results described immediately above seem to be driven precisely by increased uncertainty related to the US-Mexico trade relationship. Indeed, we consider a split sample regression where we estimate our linear probability model separately for the US and the rest of the world. The results are reported in columns 2 and 3 of Table B6. Our results show that the positive and statistically significant effect of TPU on export probabilities found for the pooled sample is driven by the behavior of Mexican exporters serving the US market. That is, the heightened trade policy uncertainty that Mexico has experienced since 2016 is specific to the bilateral relation with the US, and more broadly with NAFTA, and thus has affected the behavior of Mexican exporters in that market but not in other foreign destinations.

The results that we have presented in this section are consistent with the hypothesis that higher levels of uncertainty may increase the likelihood of exporting, particularly for participants that produce marginally exported products. Our results indicate that it is only in the foreign market in which there is uncertainty about a possible increase in non-tariff barriers that exporters have modified their export participation decision. In particular, the result from our split sample regression indicates that the result we had found in our pooled sample is not driven by the diversification efforts of Mexican exporters attempting to increase their participation in markets other than the US. That is, our results suggest that for the period studied Mexican exporters, for the most part, did not diversify their export base since we estimate that changes in trade policy uncertainty did not affect the probability of exporting a product to the rest of the world. However, it is important to remember that the products classified as “sometimes exported”, which is the sample used for our benchmark results, commands only a small share of total Mexican exports. The lion’s share of total Mexican export volumes accrues to the products classified as “always exported”, which by definition have been continuously exported throughout the period of increased trade policy uncertainty studied here.[49] Thus, while increased trade policy uncertainty has affected the export probabilities of “sometimes exported” products, we would not expect an economically significant impact of trade policy uncertainty on aggregate Mexican export volumes through the channel emphasized here. However, our evidence does not preclude the possibility that trade policy uncertainty had a significant effect on aggregate trade through other channels, for example, through its effect on the intensive margin of trade.

[49] Notice that for this set of products we cannot identify whether trade policy uncertainty has had any impact on firm-level export participation decisions, while for “sometimes exported” products our evidence suggests some change in the underlying firm-level export supply decisions otherwise trade policy uncertainty would have no impact on the export probability of these products.

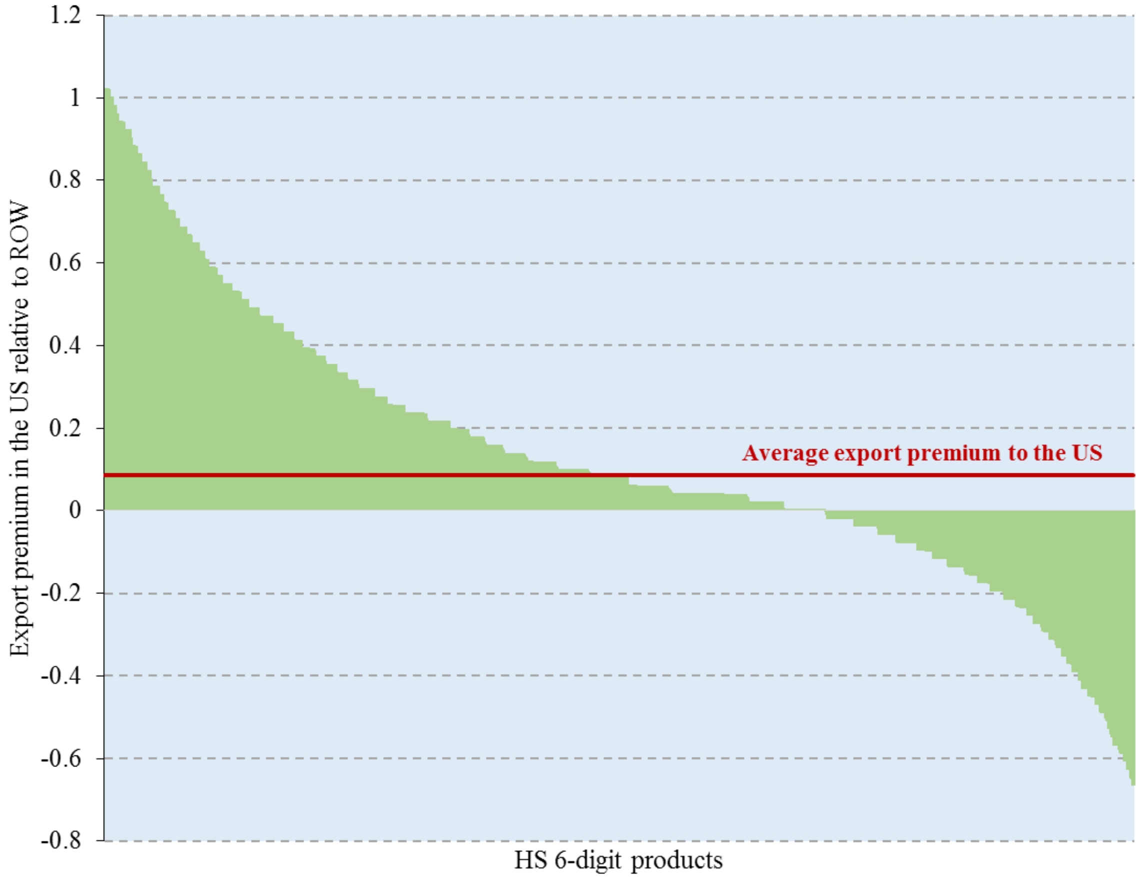
7.2.1 Figures and Tables

Figure B2. Average Probability of Exporting: USA vs ROW



Notes: This graph is based on the estimated export probabilities at the product level from our baseline specification of equation (2). The average export probability at time *t* in destination *d* corresponds to the equally weighted average of the estimated export probabilities for all HS 6-digit products in the sample. Solid black line corresponds to the average export probability to the US, the dashed line corresponds to the average export probability to the rest of the world (ROW).

Figure B3. Export premium in the US market for "sometimes exported" HS 6-digit products



Notes: This graph is constructed using the estimated product-destination fixed effects from our benchmark estimation of equation (2). For each product j, its export premium in the US market is defined as the *j,USA* fixed effect minus the *j,ROW* fixed effect. The resulting export premiums by product are presented in the graph arranged in decreasing order. For convenience we also graph the average export premium across all products. A positive export premium implies that, everything else equal product j is more likely to be exported to the US than to the rest of the world.

Table B1. Number of HS 6-digit products in Mexican exports by category

		ROW			
		Always	Never	Sometimes	Total
USA	Always	1,406	14	698	2,118
	Never	11	106	259	376
	Sometimes	253	224	1,953	2,430
	Total	1,670	344	2,910	4,924

Notes: To construct this table we use the universe of HS 6-digit products exported by Mexico in the period comprised by January 2012 to May 2017. Products in shaded areas correspond to products that are excluded from the sample that we use for our benchmark estimation, such that the total number of products included in our sample is 3,412. See main text for definition of product categories. ROW = rest of the world.

Table B2. Number of HS 6-digit Products in Mexican Exports by Sector and Destination

	USA				Rest of the World			
		Share of HS-6 digit Products (%)				Share of HS-6 digit Products (%)		
	No. of Products	Always	Never	Sometimes	No. of Products	Always	Never	Sometimes
Animal & Animal Products	199	25.63	9.55	64.82	235	13.19	22.98	63.83
Vegetable Products	305	32.46	7.21	60.33	330	17.27	14.85	67.88
Foodstuffs	177	45.76	2.82	51.41	197	43.65	8.12	48.22
Mineral Products	133	22.56	12.78	64.66	139	19.42	12.23	68.35
Chemicals & Allied Industries	658	25.99	6.53	67.48	723	35.82	7.05	57.12
Plastics / Rubbers	210	64.76	0.95	34.29	211	59.24	1.42	39.34
Raw Hides, Skins, Leather, & Furs	59	52.54	0.00	47.46	65	35.38	3.08	61.54
Wood & Wood Products	217	41.01	4.15	54.84	220	30.45	8.18	61.36
Textiles	742	35.98	3.37	60.65	763	19.79	7.21	73.00
Footwear / Headgear	46	65.22	2.17	32.61	47	38.30	4.26	57.45
Stone / Glass	189	56.61	2.65	40.74	192	36.98	8.85	54.17
Metals	548	57.12	1.28	41.61	555	41.62	3.78	54.59
Machinery / Electrical	768	59.38	0.39	40.23	770	45.06	2.34	52.60
Transportation	122	45.90	1.64	52.46	127	28.35	7.09	64.57
Miscellaneous	347	58.21	2.31	39.48	354	39.83	3.39	56.78
Total	4720	44.89	3.56	51.55	4928	33.89	6.98	59.13

Notes: To construct this table we use the universe of HS 6-digit products exported by Mexico in the period that extends from January 2012 to May 2017. See main text for definition of product categories. ROW = rest of the world.

Table B3. Distribution of Total Monthly Export Values across Product Categories (shares)

value		ROW			
		Always	Never	Sometimes	Total
USA	Always	91.70	0.97	4.30	96.98
	Never	0.04	0.00	0.04	0.08
	Sometimes	1.80	0.02	1.13	2.95
	Total	93.54	0.99	5.47	100

Notes: This table is constructed in the same manner as Table 3, except that here each cell corresponds to the average share in total export value accounted for that product category in monthly Mexican exports, rather than the number of products in that category. See main text for definition of product categories. ROW = rest of the world.

Table B4. Exposure to Trade Policy Uncertainty across Sectors

Industry	Share of Products with ETPU above sample median
Animal & Animal Products	83.66%
Mineral Products	69.26%
Vegetable Products	65.05%
Transportation	61.41%
Miscellaneous	60.90%
Machinery / Electrical	60.62%
Raw Hides, Skins, Leather, & Furs	56.14%
Foodstuffs	55.05%
Metals	49.72%
Plastics / Rubbers	48.84%
Footwear / Headgear	47.80%
Wood & Wood Products	46.72%
Stone / Glass	44.36%
Chemicals & Allied Industries	38.66%
Textiles	28.38%

Notes: To construct this table we use the universe of HS 6-digit products exported by Mexico in the period comprised by January 2012 to May 2017. Exposure to trade policy uncertainty at the product level is constructed as a weighted average of TPU at the state level using the state's share in the total employment associated with a given product. Industries are ordered in decreasing order in terms of the share of industry products that have an ETPU above the median value across all products.

Table B5. Export premium for "sometimes exported" products in the US relative to ROW by sector of economic activity

	Average export premium by HS 2-digit sector
Footwear / Headgear	0.25
Stone / Glass	0.23
Transportation	0.20
Metals	0.19
Wood & Wood Products	0.18
Machinery / Electrical	0.18
Miscellaneous	0.16
Textiles	0.15
Animal & Animal Products	0.10
Vegetable Products	0.10
Raw Hides, Skins, Leather, & Furs	0.07
Plastics / Rubbers	0.02
Foodstuffs	0.00
Mineral Products	-0.01
Chemicals & Allied Industries	-0.19
All sectors	0.09

Notes: This tale is constructed using the estimated product-destination fixed effects from our benchmark estimation of equation (2). For each product *j*, its export premium in the US market is defined as the *j,USA* fixed effect minus the *j, ROW* fixed effect. In this table we report the average export premium by broad sectors of economic activity. Each entry corresponds to the average across all products that belong to an HS 2-digit sector. Sectors are ordered in descending order according to this average export premium to the US.

Table B6. Effect of TPU on Export Participation

Dep. var.: Export status	Pooled	USA	ROW
ETPU	0.00273**	0.00328*	0.00220
	(0.00126)	(0.00179)	(0.00177)
Product-destination FE	Yes	No	No
Time-destination FE	Yes	No	No
Product FE	No	Yes	Yes
Time FE	No	Yes	Yes
Month FE	Yes	Yes	Yes
Observations	339812	173960	165852
Adjusted R2	0.786	0.752	0.817

Notes: The sample for estimation only includes the products classified as "sometimes exported". The pooled sample exports to both the USA and ROW. The split sample divides the sample according to the foreign market that a product was exported to. The results in this table are based the linear probability model of equation (2) that relates the export status of product *j* in market *d* at time *t* to product *j*'s exposure to trade policy uncertainty, where export status is a dummy equal to 1 if product *j* was exported to market *d* at time *t* and 0 otherwise. The specification includes fixed effects to control for unobservables that may affect export probabilities differentially across products, markets, and time. Robust standard errors are reported.

Table B7. Effect of TPU on Export Participation: Sample with all products

Dep. var.: Export status	All products
ETPU	0.00203**
	(0.0009584)
Product-destination FE	Yes
Time-destination FE	Yes
Product FE	No
Time FE	No
Month FE	Yes
Observations	480521
Adjusted R^2	0.8879

Notes: For this estimation we include in the sample the full universe of HS 6-digit products exported by Mexico. The results in this table are based on a linear probability model that relates export status of product *j* in market *d* at time *t* to product *j's* exposure to trade policy uncertainty. The specification includes fixed effects to control for unobservables that may affect export probabilities differentially across products, markets, and time. Robust standard errors are reported. Significance codes: * $p<0.10$, ** $p<0$.

Table B8. Effect of TPU on Export Participation: Logit

	Dependent variable: Export status
ETPU	0.0199*
	(0.0102)
Product-destination FE	No
Time-destination FE	No
Product FE	Yes
Time FE	Yes
Month FE	Yes
Observations	337058

Notes: For this estimation we estimate export probabilities via a logit model. The results in this table are based on the same sample used for our benchmark estimates that only include the products labeled as "sometimes exported". The specification includes fixed effects to control for unobservables that may affect export probabilities differentially across products, markets, and time. Robust standard errors are reported. Significance codes: * *p<0.10*, ** *p<0.*