Online Appendix

Distribution of NTMs by Type and Sector

Manufacturing sector (ISIC 2)	SPS	TBT	PSI	CTPM	QT	PCM	DR	EM
Food products and beverages	0.730	0.956	0.044	0	0.002	0.372	0	0.078
Tobacco products	0.167	1.000	0	0	0	0	0	0
Textiles	0.063	0.914	0.339	0	0	0.345	0	0.058
Wearing apparel	0	0.957	0.064	0	0	0	0	0
Tanning and dressing of leather	0	0.803	0.059	0	0	0.255	0	0
Wood products	0.563	0.635	0	0	0	0.563	0	0
Paper and paper products	0	0.828	0	0	0	0.573	0	0
Publishing and printing	0	0.667	0	0	0	0.143	0	0
Coke and refined petroleum	0	0.914	0	0	0	0	0	0
Chemicals	0.094	0.771	0	0	0	0.013	0.010	0
Rubber and plastics	0	0.885	0.038	0.019	0	0.536	0	0
Other non-metallic mineral	0.002	0.621	0	0	0	0.073	0	0
Basic metals	0	0.067	0	0.021	0	0.023	0	0
Fabricated metal products	0	0.003	0	0	0	0	0	0
Machinery and equipment	0	0.013	0	0	0	0	0	0
Officea and computing	0	0.100	0	0	0	0	0	0
Electrical machinery	0	0.005	0	0.071	0	0	0	0
Radio and communication	0	0	0	0	0	0	0	0
Medical and optical instruments	0	0.047	0	0	0	0	0	0
Motor vehicles	0	0	0	0	0	0	0	0
Other transport equipment	0	0	0	0	0	0	0	0
Furniture	0	0.056	0.008	0.004	0	0	0	0

Table A1: Share of products affected by at least one NTM by sector and NTM type in 2010
Note: SPS = sanitary and pro-sanitary measures; TBT = technical barriers to trade; PSI = pre-shipment clearance; CTPM = charges, taxes, and other para-tariff measures; QT = Quotas; PCM = price control measures; DR = distribution restrictions; EM = export measures.

Conditional Logit Model

Having only briefly outlined the conditional logit model in the main body of the manuscript, we detail the model specification in this section. This reiterates some of the main characteristics of the model described in the paper.

Combining the conditional logit model with approaches developed for events history analysis allows us to treat the underlying data as Binary Time Series Cross Section (BTSCS), which consist of realizations of zeroes and ones generated by an underlying latent variable, such that:

$$y^*_{st} = x_{s,t-1}\beta + \varepsilon_{st}$$
$$y_{st} = 1 \; if \; y^*_{s,t} > 0$$
$$y_{st} = 0 \; , \; otherwise$$

where s denotes sector and t, time; $y_{s,t}$ is a binary variable indicating whether or not an NTM was introduced in a particular sector and year; and $x_{s,t-1}$is a vector of observed covariates, including the crony presence indicator. To mitigate potential endogeneity concerns, all right-hand side variables are lagged by one year.

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There are two challenges to estimating such dynamic binary choice models: controlling for fixed effects and duration dependence. Accounting for unobserved sector-specific fixed effects in non-linear panel data models is not straightforward, as the standard way of estimating fixed effects can generate the well-known incidental parameters problem. Conditional logit models try to surmount this by conditioning on fixed effects rather than explicitly including them in the model. Conditional logit relies on units (sectors) that experience change in the response variable over time. We use a variant of this approach that involves conditioning on

the actual number of successes in a group (see Beck, 2015).[1]

Another modelling challenge arises from the possibility of temporal dependence (Beck, Katz and Tucker, 1998). Our empirical approach explicitly models duration dependence by allowing the possibility that the occurrence of an event depends both on the number of previous events and the time elapsed since the last occurrence. This is particularly relevant in our case, since the introduction of new NTMs can depend on the duration of non-eventful spells (the period during which no new NTM is introduced). To account for temporal dependence, we use time-spell polynomials that capture the length of non-events (i.e., sequence of zeroes preceding an NTM introduction) (Carter and Signorino, 2010).[2] Our models also include the number of previous NTM introductions (*Prefail*). This takes on board advice by Beck, Katz and Tucker (1998) to model the underlying hazard of an event (NTM introduction, in this case).[3] Table A2 replicates the results as shown in section 4.1 of the paper.

[1] As Beck (2015) shows this has superior finite sample properties compared to the conventional fixed effects logit.

[2] Essentially, the procedure entails construction of a series of temporal dummy variables that measure duration of prior spells of NTM introductions, and a set of time polynomials (splines) to model temporal dependence. We use the "btscs" package in Stata to estimate the spell dummies.

[3] This approach bears close resemblance to the proportional hazard models, where the conditional hazard of the event of interest happening may increase or decrease over time. The logit analysis in event history can therefore be viewed as estimating the yearly hazards of NTMs switching from zero to one. See Beck, Katz and Tucker (1998); Zorn (2000); Carter and Signorino (2010).

Table A2: NTM Introduction and Crony Activity

	(1)	(2)	(3)	(4)	(5)
	NTM Intro	NTM Intro	NTM Intro	NTM Intro	NTM Intro: First-ever
Crony presence $_{t-1}$	1.251***	1.202***	1.165***	1.310***	16.86***
	(0.395)	(0.421)	(0.430)	(0.445)	(1.460)
Imports $_{t-1}$		-0.262	-0.267	-0.291	-0.480
		(0.195)	(0.184)	(0.198)	(0.566)
Exports $_{t-1}$			-0.0304	-0.0238	0.342
			(0.158)	(0.159)	(0.399)
Tariffs $_{t-1}$				-0.481	-5.843***
				(0.313)	(1.307)
Time spell	0.684**	0.593**	0.699**	0.761**	
	(0.286)	(0.262)	(0.288)	(0.304)	
Time spell^2	-0.262**	-0.257**	-0.280**	-0.289**	
	(0.116)	(0.110)	(0.114)	(0.120)	
Time spell^3	0.0312***	0.0311***	0.0318***	0.0316***	
	(0.00949)	(0.00920)	(0.00948)	(0.00989)	
Prefail	-0.0631***	-0.0804***	-0.0723*	-0.117**	
	(0.0183)	(0.0281)	(0.0394)	(0.0527)	
Pseudo R-sq	0.321	0.319	0.285	0.296	0.554
Sectors	75	73	66	66	50
NxT	1125	1011	892	892	307

Conditional logistic fixed effects regression. Cluster-robust standard errors in parentheses.

Crony variable based on broad definition of cronies.

Prefail denotes the number of previous introductions of NTMs.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

GMM Model

Our logit analyis afforded useful insights on transition dynamics by asking whether prior presence of cronies might predict the subsequent introduction of an NTM. Another relevant dimension is to relate cronyism to the density (or overall burden) of NTM protection, as measured by the share of products in each sector subjected to NTMs. There is significant variation in the NTM coverage of products, ranging anywhere from 19% of products in a given sector subjected to NTMs to nearly 100%. About 25% of the manufacturing sectors in our sample have all their products covered by NTMs. We wish to ask whether prior presence of cronies in a sector drives some of this variation in NTM coverage across sectors. Exploring these models of NTM density has the added advantage that they permit the use of more robust empirical methods that simultaneously allow us to address temporal dependence, unobserved heterogeneity, and endogeneity concerns. To relate NTM density with cronyism we estimate dynamic GMM models of the following form:

$$y_{st} = \alpha y_{s,t-1} + \beta CronyPr_{s,t-1} + \gamma x_{s,t-1} + \varepsilon_{st}$$

where $y_{s,t}$ denotes the share of products covered by NTMs (*NTM share*), $CronyPr_{s,t-1}$ is an indicator variable capturing prior crony presence, and $x_{s,t-1}$ is the vector of control variables. To allow unobserved and time-invariant heterogeneity at the sector level and for common shocks, the error termε_{st}, includes sector-specific fixed effects (u_s) and year-specific intercepts (λ_t) besides serially uncorrelated measurement errors (v_{st}) , such that:

$$\varepsilon_{st} = \mu_s + \lambda_t + \nu_{st} \text{ for } s = 1, ...S;\ t = 1, ...T.$$

When expressed in first differences the equation takes the following form:

$$\triangle y_{st} = \alpha \triangle y_{s,t-1} + \beta \triangle CronyPr_{s,t-1} + \gamma \triangle x_{s,t-1} + \triangle \varepsilon_{st}$$

This dynamic specification eliminates the sector-specific fixed effects (u_s) through first-differencing. Consistent estimation of Equation , however, requires the use of instrumental variables to deal with the potential endogeneity of regressors and the implied correlation between differences of the lagged dependent variable and the new error term structure induced by first differencing. Subject to certain assumptions, including the requirement that the time varying component of the disturbance is independent across sectors and serially uncorrelated, dynamic panel GMM estimators permit the use of lagged levels of variables as internally generated instruments (see Arellano and Bond (1991); Roodman (2013) for de-

tails).[4] However, for highly persistent series, lagged levels may serve as weak instruments, potentially resulting in a serious finite sample bias in first-differenced estimators.

In the presence of weak instruments and short panels Blundell and Bond (1998) favour the use of the *System* GMM estimator, which combines the equations in first differences with the equations in levels (see Arellano and Bover (1995)). Subject to the validity of some additional assumptions, *System* GMM permits the use of lagged levels of the series as instruments in the first-differenced equations and lagged differences of the series as instruments in the levels equations.[5] The *System* estimator is particularly relevant for our context, since our dependent variable (*NTM share*) and main variable of interest (*CronyPr*) is possibly subjected to slow change over time. The consistency of *System* GMM crucially hinges on the validity of lagged instruments, which, in turn, is implied by the absence of serial correlation in the error term (v_{st}). The validity of instruments and the underlying moment conditions can be tested using the Sargan test of overidentifying restrictions and the separate tests for serial correlation in the differenced residuals suggested by Arellano and Bond (1991).

The tests of serial correlation also guide the choice of our precise specification, especially the number of lags to be included. We consider all time-varying regressors as endogenous, instrumenting their first differences with past levels. For the dependent variable we use values, lagged five periods or more, as potential instruments. Explanatory variables, including crony presence, are instrumented using values lagged three periods or more. Estimations are carried out on an annual sample of 75 sectors that exhibited some transition dynamics with respect to NTMs during the period, 1997-2011. Results are presented in Table A3. We begin by asking whether sectors that switch their status from non-crony to crony experience greater change in the subsequent period in the share of products covered by NTMs (*NTM share*). Column 1 provides confirmatory evidence in this regard: the coefficient on lagged crony presence is positive and statistically significant at the 1% level. Importantly, the crony effect is robust to the inclusion of key controls, such as the lagged imports, exports and MFN tariffs (all in natural logs). Our models also control for three lags of the dependent variable, coefficients on all of which are positive and statistically significant, indicating strong persistence effects in the *NTM share*.

We next relate crony presence with another measure of the intensity of NTM protection: the share of products in a sector that are covered by at least two NTMs (*NTM2 share*).

[4] Specifically, consistent estimation relies on the assumption that the initial conditions are predetermined, so that $E[y_{s1}\varepsilon_{st}] = E[CronyPr_{s1}\varepsilon_{st}] = E[x^k_{s1}\varepsilon_{st}] = 0$, for t=2,... T, s=1,...S, and k=1,...,K and it is consistent in S, the number of sectors, given T.

[5] Specifically, the following assumptions are required to hold: $E[\triangle y_{s2}u_s] = E[\triangle CronyPr_{s,t}u_s] = E[x^k_{s,t}u_s] = 0$.

The corresponding result in column 2) shows that the coefficient on lagged crony presence is again positive and significant at 1% level. A related exercise in column 3 probes whether lagged crony presence predicts changes in another measure of NTM protection, defined as the average number of different NTM chapters applied in a given sector-year (*NTM chapter*). To pass the serial correlation tests the specification now includes five lags of *NTM chapter* (two of which, lags 1 and 4, have statistically significant coefficients). Despite allowing for such temporal dependence, lagged crony presence has a positive and weakly significant impact on the intensity of NTM protection. As before, our models include several control variables for which the data is easily available. Results for these accord well with our priors. While tariffs do not have a significant impact, trade structure variables appear to exert a significant impact in most specifications. The coefficient on imports is consistently negative and statistically significant, suggesting lower levels of NTM protection for sectors reliant on imports. Model diagnostics lend support to our specifications, as we can comfortably reject the null of second-order serial correlation in all columns.

Taken together, these results present a consistent pattern, and support the contention that sectors that become crony over time tend to experience a greater burden of NTM protection, regardless of the NTM measure used. We draw greater confidence from these GMM results, since they assuage concerns about the influence of unmeasured time-invariant sector-specific effects that could be correlated with our included regressors. GMM panel data estimators are also robust to measurement error concerns and provide a possible remedy for the simultaneity problem.

However, while we use lagged crony presence to predict future changes in NTM protection, and deploy lagged values of regressors as instruments, this might leave some selection issues unaddressed, notably the possibility that prior crony presence is not completely independent of our outcome of interest (future NTM protection). For example, the underlying political process in Egypt could have led connected actors to systematically enter sectors that subsequently received higher levels of trade protection. This would prevent us from making any causal claim about the effect of cronyism on trade protection. In the empirical analysis that follows, we subject our cronyism hypothesis to a more severe test by restricting our analysis to a period during which Egypt underwent a major trade policy shift, and asking whether sectors that were previously populated by cronies disproportionately benefited from this shift.

Table A3: NTM Density and Crony Activity

	(1)	(2)	(3)
	NTM share	NTM2 share	NTM chapter
Crony presence $_{t-1}$	0.0661***	0.0675**	0.0462*
	(0.0256)	(0.0264)	(0.0281)
Imports $_{t-1}$	-0.0171***	-0.0174***	-0.0177*
	(0.00594)	(0.00602)	(0.00973)
Exports $_{t-1}$	0.00832**	0.00823**	0.000656
	(0.00368)	(0.00367)	(0.00666)
MFN $_{t-1}$	0.00519	0.00485	-0.00981
	(0.00671)	(0.00671)	(0.00927)
NxT	653	646	591
Sectors	75	75	75
Sector FEs	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes
Lags of DV	3	3	5
AR(2)	0.639	0.877	0.345

System GMM estimates with sector and year fixed effects and cluster-robust standard errors. Crony variable based on broad definition of cronies. Sample restricted to sectors with NTMs. Reported numbers for AR(2) test are p-values.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Robustness Tests 1: Narrow Definition of Cronies

In the following series of robustness tests, we reurn our baseline conditional logit (Table 3), GMM (Table 4) and DID model (Table 5) using a narrow definition of cronies. To recall, our narrow definition of cronies only includes *politicians*, that is, cronies with political connections by virtue of holding a political office, being a member of parliament, or a member in a major committee of the former National Democratic Party (NDP). This excludes the other other types of cronies, *associates* and *confidants*. The results shown in Tables A4-A6 confirm the robustness of our findings to different ways of measuring crony activity across sectors. Only in column 3, Table A5 our crony variable fails to reach significance (p=0.27), which is probably due to some remaining serial correlation as indicated by the low p-value (p=0.07) of the AR(2) test.

Table A4: NTM Introduction and Crony Activity – Narrow Definition of Cronies

	(1)	(2)	(3)	(4)	(5)
	NTM Intro	NTM Intro	NTM Intro	NTM Intro	NTM Intro: First-ever
Crony presence $_{t-1}$	1.251***	1.202***	1.165***	1.310***	16.86***
	(0.395)	(0.421)	(0.430)	(0.445)	(1.460)
Imports $_{t-1}$		-0.262	-0.267	-0.291	-0.480
		(0.195)	(0.184)	(0.198)	(0.566)
Exports $_{t-1}$			-0.0304	-0.0238	0.342
			(0.158)	(0.159)	(0.399)
Tariffs $_{t-1}$				-0.481	-5.843***
				(0.313)	(1.307)
Time spell	0.684**	0.593**	0.699**	0.761**	
	(0.286)	(0.262)	(0.288)	(0.304)	
Time spell^2	-0.262**	-0.257**	-0.280**	-0.289**	
	(0.116)	(0.110)	(0.114)	(0.120)	
Time spell^2	0.0312***	0.0311***	0.0318***	0.0316***	
	(0.00949)	(0.00920)	(0.00948)	(0.00989)	
Prefail	-0.0631***	-0.0804***	-0.0723*	-0.117**	
	(0.0183)	(0.0281)	(0.0394)	(0.0527)	
Pseudo R-sq	0.321	0.319	0.285	0.296	0.554
Sectors	75	73	66	66	50
NxT	1125	1011	892	892	307

Conditional logistic fixed effects regression. Cluster-robust standard errors in parentheses

Crony variable based on narrow definition of cronies.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A5: NTM Density and Crony Activity – Narrow Definition of Cronies

	(1) NTM share	(2) NTM2 share	(3) NTM chapter
Crony presence $_{t-1}$	0.0626***	0.0635***	0.0311
	(0.0229)	(0.0242)	(0.0283)
Imports $_{t-1}$	-0.0149**	-0.0153***	-0.0180*
	(0.00588)	(0.00591)	(0.00987)
Exports $_{t-1}$	0.00658*	0.00679*	0.00192
	(0.00357)	(0.00360)	(0.00628)
MFN $_{t-1}$	0.00624	0.00617	-0.00991
	(0.00676)	(0.00681)	(0.00960)
Observations	653	646	591
Sectors	75	75	75
Sector FEs	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes
Lags of DV	3	3	5
AR(2)	0.659	0.986	0.07

System GMM estimatesl with sectors and year fixed effects and cluster-robust standard errors. Crony variable based on narrow definition of cronies. Sample restricted to sectors with NTMs. Reported numbers for AR(2) test are p-values.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A6: Results for Difference-in-Difference Model – Narrow Definition of Cronies

	(1)	(2)	(3)	(4)	(5)	(6)
	NTM cum	NTM cum	NTM new	NTM new	NTM cum	NTM new
Initial crony count x Post	0.153**	0.143**	0.148**	0.174**	0.118*	0.074**
	(0.0663)	(0.0652)	(0.0632)	(0.0678)	(0.0626)	(0.0292)
Two-period	No	No	No	No	Yes	Yes
Controls	No	Yes	No	Yes	Yes	Yes
Sector trends	Yes	Yes	Yes	Yes	Yes	Yes
Adj R-sq	0.751	0.774	0.437	0.441	0.876	0.616
Sectors	119	119	119	119	119	119
NxT	1309	1102	1309	1102	238	238

Observations are at the sector-year level. The dependent variable is either the cumulative number of NTMs (NTM cum) or number of new NTMs applied in a given sector-year (NTM new). All regressions include year and sector fixed effects. Coefficients are reported with robust standard errors, clustered at the sector level, in parentheses.
The estimation period is 2001-2011. Post dummy is equal to 1 if year is greater than 2004 and 0, otherwise. Controls include total imports, exports and MFN tariffs, all measured in natural log and weighted by number of products.
Crony variable is based on narrow definition of cronies.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Robustness Tests 2: DID Model

To probe the robustness of our DID model, we present six types of tests: (i) an estimation of NTM subtypes; (ii) the use of a treatment dummy instead of continuous measure of treatment; (iii) the inclusion of additional control variables from the UNIDO Indstat dataset; (iv) the restriction of our sample to only those sectors that experienced a tariff cut in 2004; (v) a redefinition of treated sectors bringing the cut-off year between treated an untreated sectors forward to 1990; (vi) the inclusion of our instrumental variables as normal controls in the baseline regression to statistically demonstrate the validity of the exclusion restriction. In addition, we provide further details on our Tunisia crony data, including a number of descriptive statistics.

NTM subtypes

In Tables A7 and A8, we replicate our baseline DID model for NTM subtypes. The test reveals that crony sectors received more NTMs in the form of technical barriers to trade (TBT), pre-shipment inspections (PSI), and to a lesser extent price control measures (PCM). Other types of NTMs do not seem to be affected.

Table A7: Results for Difference-in-Difference Mode by NTM Subtype (cumulative)

	(1)	(2)	(3)	(4)	(5)	(6)
	SPS	TBT	PSI	CTPM	PCM	EM
Initial crony count x Post	0.0187	0.0956**	0.0254**	-0.00266	0.00510	0.000370
	(0.0180)	(0.0469)	(0.0123)	(0.00345)	(0.0113)	(0.000361)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Sector trends	Yes	Yes	Yes	Yes	Yes	Yes
Adj R-sq	0.388	0.795	0.373	0.101	0.529	0.0276
Sectors	119	119	119	119	119	119
NxT	1102	1102	1102	1102	1102	1102

Observations are at the sector-year level. The dependent variable is the cumulative number of NTM subtypes applied in a given sector-year(NTM new). NTM subtypes Quotas and DR could not be estimated. All regressions include year and sector fixed effects. Coefficients are reported with robust standard errors, clustered at the sector level, in parentheses. The estimation period is 2001-2011. Post dummy is equal to 1 if year is greater than 2004 and 0, otherwise. Controls include total imports, exports and MFN tariffs, all measured in natural log and weighted by number of products. Crony variable is based on broad definition of cronies.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A8: Results for Difference-in-Difference Mode by NTM Subtype (new)

	(1)	(2)	(3)	(4)	(5)	(6)
	SPS	TBT	PSI	CTPM	PCM	EM
Initial crony count x Post	0.00853	0.143***	0.0339**	-0.00774	0.0250*	0.00395
	(0.0178)	(0.0515)	(0.0141)	(0.00841)	(0.0127)	(0.00764)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Sector trends	Yes	Yes	Yes	Yes	Yes	Yes
Adj R-sq	0.126	0.507	0.0833	0.0352	0.132	0.0307
Sectors	119	119	119	119	119	119
NxT	1102	1102	1102	1102	1102	1102

Observations are at the sector-year level. The dependent variable is the number of new NTM subtypes applied in a given sector-year(NTM new). NTM subtypes Quotas and DR could not be estimated. All regressions include year and sector fixed effects. Coefficients are reported with robust standard errors, clustered at the sector level, in parentheses. The estimation period is 2001-2011. Post dummy is equal to 1 if year is greater than 2004 and 0, otherwise. Controls include total imports, exports and MFN tariffs, all measured in natural log and weighted by number of products. Crony variable is based on broad definition of cronies.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Treatment dummy

In Table A9, we replicate our baseline DID model using a dummy indicator instead of a continuous measure of treatment. To recall, we consider sectors as treated by they were populated by cronies by 1998, that is, six year before the EU-Egypt trade agreement. On the whole, the results support our main finding that crony sectors benefited significantly more from NTM protection in the wake of the EU-Egypt trade agreement than non-crony sectors.

The results are particularly strong when using the number of NTMs introduced as the dependent variable, both in the annual panel and the two-period model. When using the cumulative number of NTMs, we recover our main result in the annual panel, albeit slightly weaker than our results with a continuous treatment measures. Only in the two-period model in column 5, the interaction term ceases to be significant (p=0.27) while showing the expected direction of sign. We would like to point out, however, that the cumulative measure of NTMs contains, by construction, less over-time variation, which is further compressed when collapsing the measure in a two-period model. In addition, our treatment dummy further compresses variation in the data, which, in combination, entails the loss of precision as shown by the increasing standard error of the interaction term. Given that all other permutations of the model in Table A9 show a significant finding, we are not too concerned by non-finding in column 5.

Table A9: Results for Difference-in-Difference Model – Treatment Dummy

	(1)	(2)	(3)	(4)	(5)	(6)
	NTM cum	NTM cum	NTM new	NTM new	NTM cum	NTM new
Initial crony dummy x Post	0.230*	0.262*	0.328**	0.355**	0.176	0.153**
	(0.161)	(0.155)	(0.138)	(0.151)	(0.156)	(0.075)
Two-period	No	No	No	No	Yes	Yes
Controls	No	Yes	No	Yes	Yes	Yes
Sector trends	Yes	Yes	Yes	Yes	Yes	Yes
Adj R-sq	0.749	0.771	0.436	0.439	0.868	0.611
Sectors	119	119	119	119	119	119
NxT	1309	1102	1309	1102	238	238

Observations are at the sector-year level. The dependent variable is either the cumulative number of NTMs (NTM cum) or number of new NTMs applied in a given sector-year (NTM new). All regressions include year and sector fixed effects. Coefficients are reported with robust standard errors, clustered at the sector level, in parentheses.
The estimation period is 2001-2011. Post dummy is equal to 1 if year is greater than 2004 and 0, otherwise. Controls include total imports, exports and MFN tariffs, all measured in natural log and weighted by number of products.
Crony variable is based on broad definition of cronies.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

UNIDO controls

As a complementary exercise, we also explore the relevance of UNIDO's manufacturing indicators available for ISIC-4 classifications. The INDSTAT4 database (UNIDO, 2013) provides a variety of sector-level indicators that could be included as plausible controls in our regression models. To explore possible size effects, we successively evaluate the effect of the total number of employees, number of establishments, and employees per establishment. Output and value-added per establishment are added as other relevant correlates. Finally, we test whether the sectoral concentration of employment or output drives non-tariff protection in a sector.[6] Since the UNIDO data has patchy coverage and not available annually, we deploy these variables as additional controls in our two-period DID set-up. The results for both models of *NTM cum* and *NTM new* are reported in Tables A10 and A11 below. Reassuringly, the inclusion of these additional controls does not alter our conclusions.[7] In fact, in most specifications, the coefficient on treatment size interaction with *Post* remains statistically significant at 1% level.

[6]Employment concentration is defined as employees in an ISIC-4 sector as a share of total manufacturing sector employment. Similarly, output concentration is defined as output in an ISIC-4 sector as a share of total manufacturing output.

[7]Apart from employment concentration, which has a negative and statistically significant impact on measures of non-tariff protection, none of the UNDO controls turn as important predictors.

Table A10: DID Model with UNIDO controls: NTM cum

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Initial crony count x Post	0.152**	0.160***	0.181***	0.172***	0.169***	0.159***	0.150**	0.170***
	(0.0584)	(0.0599)	(0.0598)	(0.0592)	(0.0579)	(0.0576)	(0.0598)	(0.0592)
Employees	0.0570							0.0922
	(0.0783)							(0.116)
Establishments		0.238						0.0890
		(0.154)						(0.195)
Output per firm			-0.0642					
			(0.0564)					
Employees per firm				-0.192				
				(0.143)				
Value-added per firm					-0.0760			
					(0.0822)			
Employees concentration						-66.34***		-71.14***
						(18.65)		(17.46)
Output concentration							-4.239	3.256
							(8.940)	(5.636)
Observations	237	237	224	228	228	237	237	237
R-squared	0.865	0.866	0.897	0.878	0.877	0.886	0.864	0.889
Sectors	119	119	115	115	115	119	119	119

Observations are at the sector-period level. The dependent variable is the cumulative number of NTMs applied in a given sector-period (NTM cum). All regressions include period and sector fixed effects, and sector-specific time trends. Crony variable is based on broad definition of cronies. The estimation period is 2001-2011. Post dummy is equal to 1 if period is greater than 2004 and 0, otherwise. All models include average MFN tariff weighted by number of products. All variables are expressed in natural logs. Cluster-robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A11: DID Model with UNIDO controls: NTM new

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Initial crony count x Post	0.0774***	0.0785***	0.0830***	0.0870***	0.0893***	0.0772***	0.0730**	0.0761***
	(0.0291)	(0.0289)	(0.0307)	(0.0287)	(0.0290)	(0.0295)	(0.0294)	(0.0288)
Employees	0.0341							0.0651
	(0.0234)							(0.0403)
Establishments		0.0703						-0.0657
		(0.0726)						(0.115)
Output per firm			-0.0330					
			(0.0288)					
Employees per firm				0.0201				
				(0.0513)				
Value-added per firm					-0.0186			
					(0.0270)			
Employment concentration						-14.13		-18.46*
						(11.19)		(10.68)
Output concentration							2.880	5.187
							(4.205)	(3.152)
Observations	237	237	224	228	228	237	237	237
R-squared	0.608	0.607	0.633	0.630	0.631	0.619	0.607	0.632
Sectors	119	119	115	115	115	119	119	119

Observations are at the sector-period level. The dependent variable is the number of new NTMs applied in a given sector-period (NTM new). All regressions include period and sector fixed effects, and sector-specific time trends. Crony variable is based on broad definition of cronies. The estimation period is 2001-2011. Post dummy is equal to 1 if period is greater than 2004 and 0, otherwise. All models include average MFN tariff weighted by number of products. All variables are expressed in natural logs. Cluster-robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Sample restriction

In Table A12, we rerun our baseline DID model while restricting the sample to those sectors that witnessed a tariff cut in 2004 – the year of the EU-Egypt trade agreement . The logic behind this is that the trade agreement can only be considered a fully exogenous shock for those sectors whose tariffs are cut following the agreement. The results are robust to this sample restriction in all but two cases (column 2, 5), where they fail to reach conventional levels of statistical significance (p=0.127 and 0.158 respectively). This reflects a consistent trend across all DID models which shows somewhat weaker results for the *NTM cum* measure, especially when used in a two-period setup (see previous section). We find it reassuring, however, that in column 1, the interaction term reaches, albeit weak, significance while including sector and year fixed effects as well as sector time trends. The loss of significance in column 2 is mostly attributable to the loss of observations when including further controls, which drop from 957 to 812. The same is also true for column 5: when we ran the two-period model on NTM cum without controls, the p-value of the interaction term drops to 0.058.[8] This means that the loss of significance in columns 2 and 5 is most probably driven by listwise deletion.

[8]Results available upon request.

Table A12: Results for Difference-in-Difference Model – Sample Restriction

	(1)	(2)	(3)	(4)	(5)	(6)
	NTM cum	NTM cum	NTM new	NTM new	NTM cum	NTM new
Initial crony dummy x Post	0.127*	0.110	0.140**	0.148**	0.110	0.068*
	(0.070)	(0.071)	(0.0690)	(0.072)	(0.077)	(0.039)
Two-period	No	No	No	No	Yes	Yes
Controls	No	Yes	No	Yes	Yes	Yes
Sector trends	Yes	Yes	Yes	Yes	Yes	Yes
Adj R-sq	0.755	0.778	0.466	0.489	0.862	0.639
Sectors	87	87	87	87	87	87
NxT	957	812	957	812	174	174

Observations are at the sector-year level. The sample is restricted to those sectors that witnessed a tariff cut in 2004. The dependent variable is either the cumulative number of NTMs (NTM cum) or number of new NTMs applied in a given sector-year (NTM new). All regressions include year and sector fixed effects. Coefficients are reported with robust standard errors, clustered at the sector level, in parentheses. The estimation period is 2001-2011. Post dummy is equal to 1 if year is greater than 2004 and 0, otherwise. Controls include total imports, exports and MFN tariffs, all measured in natural log and weighted by number of products. Crony variable is based on broad definition of cronies.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Bringing the crony treatment forward

In this robustness test, we bring the classification of treated sectors further back to 1990. Defining treated sectors as those exposed to crony presence by 1990, nearly fourteen years before the EU trade agreement, we re-estimate our core DID specification. This yields a highly robust set of findings as displayed in Table A13 below. The parallel trends assumption also holds for this specification of cronies as shown in Figure A1.

Table A13: Bringing the treatment classification forward to 1990

	(1) NTM cum	(2) NTM cum	(3) NTM new	(4) NTM new
Initial crony count x Post	0.315**	0.309**	0.270**	0.306**
	(0.157)	(0.153)	(0.118)	(0.129)
Controls	No	Yes	No	Yes
Sector trends	Yes	Yes	Yes	Yes
Adj R-sq	0.755	0.778	0.437	0.441
Sectors	119	119	119	119
Observations	1,309	1,102	1,309	1,102

Observations are at the sector-year level. The dependent variable is either the cumulative number of NTMs (NTM cum) or number of new NTMs applied in a given sector-year (NTM new). All regressions include year and sector fixed effects. Coefficients are reported with robust standard errors, clustered at the sector level, in parentheses. The estimation period is 2001-2011. Post dummy is equal to 1 if year is greater than 2004 and 0, otherwise. Controls include total imports, exports and MFN tariffs, all measured in natural log and weighted by number of products. Crony variable is based on broad definition of cronies. A sector is treated as crony if it was exposed to cronies until the year 1990.

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

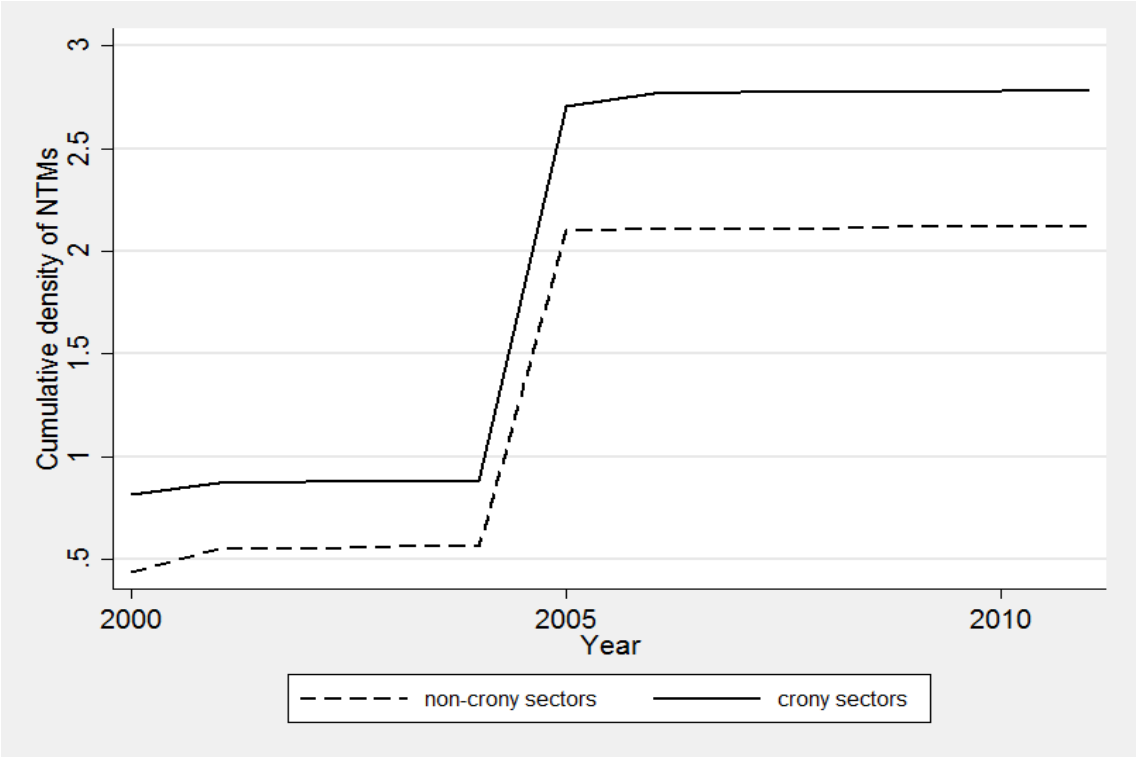

Figure A1: Parallel trends plots using 1990 crony cut-off

Exclusion restriction

In Table A14, we statistically test the validity of the exclusion restriction of our IV model by successively adding our instruments – *Neighbour-crony ratio* and *CronyTunisia* – as controls to our baseline annual DID model. We also test if trade protection in neighbouring sectors has any spill-over effect, which would invalidate the use of the neighbour-crony instrument. The results suggest that neither of the two instruments nor the level of trade protection in other sectors are affecting NTM protection other than through the crony variable. This is particularly reassuring in the case of the *Neighbour-crony ratio* as alleviates concerns about spill-over effects from crony activity in neighbouring sectors.

Table A14: Results for Difference-in-Difference Model – Test of Exclusion Restriction

	(1)	(2)	(3)
	NTM cum	NTM cum	NTM cum
Initial crony count x Post	0.182*	0.120*	0.109
	(0.102)	(0.072)	(0.075)
Neighbour-crony ratio x Post	-0.080		
	(0.214)		
Neighbour-NTM cum x Post		0.034	
		(0.025)	
CronyTunisia x Post			0.143
			(0.216)
Two-period	No	No	No
Controls	Yes	Yes	Yes
Sector trends	Yes	Yes	Yes
Adj R-sq	0.800	0.783	0.778
Sectors	60	87	87
NxT	560	812	812

Observations are at the sector-year level. The dependent variable is either the cumulative number of NTMs (NTM cum) or number of new NTMs applied in a given sector-year (NTM new). All regressions include year and sector fixed effects. Coefficients are reported with robust standard errors, clustered at the sector level, in parentheses. The estimation period is 2001-2011. Post dummy is equal to 1 if year is greater than 2004 and 0, otherwise. Controls include totalimports, exports and MFN tariffs, all measured in natural log and weighted by number of products. Crony variable is based on broad definition of cronies.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Tunisian crony data

To collect data on crony activity in Tunisia, we adopted the following procedure: first, we compiled an initial list of politically connected entrepreneurs based on internal documents of the German Trade Invest (2011), a market research and consultancy company based in Tunis, and the German-Tunisian Chamber of Commerce (2011). The information contained in these reports relies on in-depth research carried out by their staff.[9] We then collected information on their companies and their activities at the ISIC4 level (Rev. 3.1), using the Orbis database (Bureau van Dijk, 2013). This results in a dummy indicator taking the value of 1 whenever a crony is active in a sector and 0 otherwise. Table A15 summarises the presence of cronies for each ISIC2 manufacturing sector in Tunisia and Egypt.

Manufacturing Sector	Tunisia	Egypt
Food products and beverages	47	59
Tobacco products	0	80
Textiles	0	70
Wearing apparel	50	50
Tanning and dressing of leather	67	67
Wood products	80	40
Paper and paper products	33	32
Publishing and printing	0	56
Coke and refined petroleum products	0	30
Chemicals	11	62
Rubber and plastics	33	68
Other non-metallic mineral products	25	95
Basic metals	50	75
Fabricated metal products	60	65
Machinery and equipment	0	33
Office, accounting and computing machinery	0	0
Electrical machinery	0	68
Radio, television and communication equipment	33	78
Medical, precision and optical instruments	0	54
Motor vehicles	67	95
Other transport equipment	0	14
Furniture	17	68

Table A15: Percentage of sectors (ISIC4) with crony activity by manufacturing sector (ISIC2)

[9] We are particularly grateful to Fausi Najjar at the German Trade Invest for generously sharing his data.

References

Arellano, Manuel and Olympia Bover. 1995. "Another Look at the Instrumental Variable Estimation of Error-Components Models." *Journal of Econometrics* 68(1):29–51.

Arellano, Manuel and Stephen Bond. 1991. "Some Tests of Specification for Panel dData: Monte Carlo Evidence and an Application to Employment Equations." *The Review of Economic Studies* 58:277–297.

Beck, Nathaniel L. 2015. "Estimating grouped data models with a binary dependent variable and fixed effects: What are the issues?".

Beck, Nathaniel L., Jonathan N. Katz and Richard Tucker. 1998. "Taking Time Seriously: Time-Series-Cross-Section Analysis with a Binary Dependent Variable." *American Journal of Political Science* 42(4):1260–1288.

Blundell, Richard and Stephen Bond. 1998. "Initial Conditions and Moment Restrictions in Dynamic Panel Data Models." *Journal of Econometrics* 87(1):115–143.

Bureau van Dijk. 2013. "Orbis Database.".
URL: *https://orbis.bvdinfo.com/*

Carter, David B. and Curtis Ss Signorino. 2010. "Back to the Future: Modeling Time Ddependence in Bbinary Data." *Political Analysis* 18:271–292.

German Trade Invest. 2011. The Presence of the Ben Ali/Trabelsi Family in the Tunisian Economy. Technical report German Trade Invest Tunis: .

German-Tunisian Chamber of Commerce. 2011. Ben Ali and the 40 Thieves. Technical report Tunis: .

Roodman, David. 2013. "XTABOND2: Stata module to extend xtabond dynamic panel data estimator.".
URL: *http://ideas.repec.org/c/boc/bocode/s435901.html*

UNIDO. 2013. "INDSTAT4 Industrial Statistics Database.".
URL: *http://www.unido.org/en/resources/statistics/statistical-databases.html*

Zorn, Christopher J. W. 2000. "Modeling Duration Dependence." *Political Analysis* 8(4):367–380.