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Appendix A Definition and Data Sources of Control Variables

A.1 Prefecture-Level Characteristics

The prefecture-level characteristics used as controls in the regressions are listed below. All the variables are measured in 1990. Data on GDP per capita are obtained from the China City Statistical Yearbook of 1990.

The following four variables are calculated using the 1990 China population census.

- Years of education: Prefecture's average years of education of population aged above six.
- Population age: Prefecture's average population age.
- Fertility rate: Prefecture's average births to women aged 20 to 45 years old.
- Child population: Prefecture's total population under age 18.

A.2 Policy Controls

Other policy controls used in the main regressions are listed below.

- Output tariff: Data on output tariff at the HS-6 product level are obtained from the World Integrated Trade Solution (WITS) database. The HS-6 product level data are aggregated to 3-digit industry classification in the 1990 census data, using a concordance table between the Chinese Industrial Classification (CIC) system and HS codes. The simple average tariff for each 3-digit industry is then computed. The prefectures' exposure to output tariff is measured using the 1990 employment-share-weighted-average tariff in 2001 across 3-digit industries in the prefecture as in Eq. (1), i.e., $\tau_p^o = \sum_j S_{jp}^{1990} \times \tau_{j,2001}^o$. Here, $\tau_{j,2001}^o$ is output tariff of industry j in 2001. The tariff measure τ_p^o is then interacted with the post-PNTR dummy and included in the specification.

- Input tariff: We first calculate the 3-digit industry-level input tariff as a weighted average of the industry-level output tariff, using as the weight the share of inputs in the output value from the China input-output table for 1997. Specifically, input tariff $\tau_j^i = \sum_k \tau_k^o \times \omega_{kj}$, where τ_k^o is output tariff of industry k, and ω_{kj} is the share of inputs from industry k used by industry j, using the 1997 China input-output table. The prefectures' exposure to input tariff as the 1990 employment-share-weighted-average input tariff in 2001 across 3-digit industries in the prefecture as in Eq. (1), i.e., $\tau_p^i = \sum_j S_{jp}^{1990} \times \tau_{j,2001}^i$. We then interact the input tariff τ_p^i with the post-PNTR dummy and include the interaction in the specification.

- External tariff: Data on industry-level external tariff is measured as a weighted average of the destination country's tariffs on China's imports, using China's exports to each destination country as the weight. Specifically, external tariff $\tau_j^e = \sum_d \tau_{dj}^e \times \frac{Y_{dj}}{Y_d}$, where τ_{dj}^e is country d's tariffs on Chinese imports of industry j, Y_{dj} is China's exports of industry j to destination country d, and Y_d is China's exports to the destination country d. The export data come from the United Nations Comtrade Database. We then compute prefectures' exposure to the external tariff as the 1990 employment-share-weighted-average external tariff in 2001 across 3-digit industries in the prefecture as in Eq. (1), i.e., $\tau_p^e = \sum_j S_{jp}^{1990} \times \tau_{j,2001}^e$, and then interact the external tariff τ_p^e with the post-PNTR dummy and include it in the specification.

- Input relationship-specific index: We proxy barriers to investment in China using an input relationship-specificity index proposed by Nunn (2007). Based on the classifications in Rauch (1999), Nunn (2007) considers goods that are neither reference priced nor sold on exchange markets to be relationship-specific goods and computes the proportion of relationship-specific inputs, for each product in 1987 US input-output table. The 1987 IO industry is mapped to the HS 10-digit product level using concordance provided by the Bureau of Economic Analysis and then averaged to the HS-6 product level. The measure is converted to a 3-digit industry classification in the 1990 China census data, using a concordance table between CIC system and HS codes. We then calculate prefectures' exposure using the 1990 employment-share-weighted-average input relationship-specific index across 3-digit industries in the prefecture as in Eq. (1). The measure is interacted with the post-PNTR dummy and included in the specification.

- MFA exposure: We use data on the Multifiber Arrangement (MFA) "quota-bound" product at the HS 6-digit product level in year 2001 from Khandelwal et al. (2013). The HS 6-digit product level is mapped to the 3-digit Chinese industry level in the census 1990 using the concordance between CIC system and HS codes. Based on these 3-digit industry-level data, we construct a prefecture-level exposure to MFA using employment-share-weighted "quota-bound" product across 3-digit industries in the prefecture as in Eq. (1). The measure is interacted with the post-PNTR dummy and included in the specification.

- NTR rate: We use the U.S. import tariff rate at the HS-6 product level as a measure of NTR tariff rates. The tariff data are obtained from the WITS database, and then aggregated up to the 3-digit industry classification in the 1990 census data using a concordance table between CIC system and HS codes. The prefecture-level exposure to NTR tariff is computed using employment-share-weighted US import tariff rates in 2001 across 3-digit industries in the prefecture as in Eq. (1). The measure is then interacted with the post-PNTR dummy and is included in the specification.

Appendix B Causal Analyses

B.1 Relationships between Average, Conditional, and Marginal Effects

Section 3 of the main paper defines three causal effects of interest. The average effects are ATT_t, ATE_t; the conditional effects are $ATT_t(m)$ in (3) and $ATE_t(m)$ in (4); and the marginal effects are $MATT_t(m)$ and $MATE_t(m)$ in (5).

The relationship between average and conditional effect is simple. We can obtain the average effects ATT_t and ATE_t by integrating the conditional effects $ATT_t(m)$ in (3) and $ATE_t(m)$ in (4) over the associated probability distribution of M. For instance, the average causal effect is given by:

$$ATE_t \equiv E(Y_t(1) - Y_t(0)) = \int E(Y_t(1, m) - Y_t(0, m)|M = m)dF_M(m) = \int ATE_t(m)dF_M(m),$$

while the average treatment effect on the treated is:

$$\begin{aligned} ATT_t \equiv E(Y_t(1) - Y_t(0)|D = 1) &= \int E(Y_t(1, m) - Y_t(0, m)|M = m, D = 1)dF_{M|D=1}(m), \\ &= \int ATT_t(m)dF_{M|D=1}(m), \end{aligned}$$

where $F_M(m) = P(M \le m)$ denotes the cumulative distribution function of the moderator and $F_{M|D=1(m)} = P(M \le m|D = 1)$ is the conditional cumulative distribution.

The relationship between average and marginal effects is not as straightforward. Consider the case of a continuous moderator M whose support is given by the interval $\mathcal{M} = [\underline{m}, \overline{m}]$. Note that the integral of $MATT_t$ or $MATE_t$ in (5) over the support of the moderator M does not deliver ATT_t or ATE_t. In the case of $MATE_t$, we have that:

$$\int_{\underline{m}}^{\overline{m}} MATE_t(m)dm = ATE_t(\overline{m}, \overline{m}) - ATE_t(\underline{m}, \underline{m}). \tag{21}$$

The next proposition clarifies the relationship between the average, marginal and conditional effects:

Proposition P.1. Consider a DiD model where **A.1**–**A.2** holds, M is a continuous random variable in $[\underline{m}, \overline{m}]$, and $ATE_t(m)$ in (4) be a differentiable function. Then for any value $m^* \in [\underline{m}, \overline{m}]$ we have that:

$$ATE_t = \int_{\underline{m}}^{\overline{m}} MATE_t(m)\Big(\mathbf{1}[m > m^*]\,(1 - F_M(m)) - \mathbf{1}[m < m^*]F_M(m)\Big)dm + ATE_t(m^*|m^*). \tag{22}$$

If $ATT_t(m)$ in (3) is differentiable, then (22)–(24) also hold if we were to replace ATE_t, $MATE_t$, $ATE_t(m^*)$, $F_M(m)$ by ATT_t, $MATT_t$, $ATT_t(m^*)$, $F_{M|D=1}(m)$ respectively.

Proposition P.1 shows that is it possible to express the average treatment effect in terms of the marginal response $MATE_t$ and the conditional effect $ATE_t(m|m)$. The proposition states that for any value m^* of the moderator, the difference between ATE_t and the conditional effect $ATE_t(m^*)$ can be expressed as a weighted average of the marginal effect $MATE_t(m)$ over the moderator's probability distribution. Moreover, the weights for $MATE_t(m)$ such that $m > m^*$ are positive and given by $(1 - F_M(m))$, while the weights for $MATE_t(m)$ such that $m > m^*$ are the negative values of the CDF $F_M(m)$.

Now suppose there are values of the moderator that make the treatment ineffective. Notationally, this means that there is a set $\mathcal{M}_0 \subset \mathcal{M}$ such that for any value $m_0 \in \mathcal{M}_0$ we have the following:

$$Y_{it}(d, m_0) = Y_{it}(0, m_0); d \in \{0, 1\} \text{ for all units } i \in \mathcal{I}.$$

This means that [36]

In our empirical setting, M moderates the impact of trade tariffs on the economy of the Chinese prefecture and D is the policy of tariff changes. The economic impact of the policy depends on the share of the prefecture's industries targeted by the tariff change. The policy has limited effect on prefectures with closed economies or those whose industries are not targeted by the policy. In this case $M_i = 0 \equiv m_0$.

A consequence of Proposition P.1 is that for any value $m_0 \in \mathcal{M}_0 \subset [\underline{m}, \overline{m}]$ we have that:

$$ATE_t = \int_{\underline{m}}^{\overline{m}} MATE_t(m)\Big(\mathbf{1}[m > m_0]\,(1 - F_M(m_0)) - \mathbf{1}[m < m_0]F_M(m)\Big)dm. \tag{23}$$

$$\text{Moreover, if } \underline{m} \in \mathcal{M}_0, \text{ then } ATE_t = \int_{\underline{m}}^{\overline{m}} MATE_t(m)\,(1 - F_M(m))\,dm. \tag{24}$$

The equations above mean that if we set m^* to a value m_0 where no treatment moderation occurs, then ATE can be expressed as a function of its marginal effect as in equation (23). The weights of this equation can be further simplified into equation (24) if the lowest value of the moderator $\underline{m}$ renders the treatment ineffective.

B.2 Conditional Parallel Trend does not Identify Average Effects

A common goal of the empirical evaluation is to examine how the moderator affects the effect of the treatment on the outcomes. The natural procedure to assess the impact of the moderator is to compare the treatment effects across the values of the moderator M. The following notation is useful to investigate this comparison:

$$ATT_t(m|m') = E(Y_t(1, m) - Y_t(0, m)|D = 1, M = m'),$$

[36] If we set the moderator value m_0 to zero, than we have $Y_{it}(d, 0) = Y_{it}(0, 0); d \in \{0, 1\}$ for all units $i \in \mathcal{I}$.

which denotes the treatment on the treated when we fix the moderator at the value m conditioning on the units i that share the moderator value of $M_i = m'$. According to the notation of the main paper, we have that $ATT_t(m|m) = ATT_t(m)$.

The Conditional Parallel Trend Assumption **A.3** enable us to decompose the difference between the treated on the treated as:

$$
\begin{aligned}
& ATT_t(m|m) - ATT_t(m'|m') && (25)\\
&= E(Y_t(1,m) - Y_t(0,m)|D=1, M=m) - E(Y_t(1,m') - Y_t(0,m')|D=1, M=m') && (26)\\
&= \underbrace{E(Y_t(1,m) - Y_t(0,m)|D=1, M=m) - E(Y_t(1,m') - Y_t(0,m')|D=1, M=m)}_{ATT_t(m|m) - ATT_t(m'|m)} && (27)\\
&+ \underbrace{E(Y_t(1,m') - Y_t(0,m')|D=1, M=m) - E(Y_t(1,m') - Y_t(0,m')|D=1, M=m')}_{ATT_t(m'|m) - ATT_t(m'|m')}. && (28)
\end{aligned}
$$

In summary, we can express the difference of conditional ATT parameters as:

$$
ATT_t(m|m) - ATT_t(m'|m') = \underbrace{ATT_t(m|m) - ATT_t(m'|m)}_{\text{Effect Difference}} + \underbrace{ATT_t(m'|m) - ATT_t(m'|m')}_{\text{Selection Bias on the Moderator}}. \quad (29)
$$

The decomposition above shows that the difference between the treated on the treated effects comprises two terms. The first term is the difference in the treatment effect when we fix the moderator at different levels for the same units i such that $M_i = m$. It accounts for the change in the treatment-on-the-treated effect due to a shift in the moderator.

The second term in (29) is due to selection bias. It accounts is the change in the treatment on the treated effect between two sets of units. The parameter $ATT_t(m'|m)$ denotes the treatment effect when we fix the mediator M to the value $m' \in \mathcal{M}$ for units i that share the moderator value m. The parameter $ATT_t(m'|m)$ also fixes the mediator M to the value $m' \in \mathcal{M}$, however this effect is evaluated for a different set of units i that share the moderator value m'.

The main conclusion of the decomposition (29) is that the Conditional Parallel Trends Assumption **A.3** is not sufficiently strong to render a clear causal interpretation of the differences between the treatment on the treated effects.

The Conditional Parallel Trend Assumption **A.3** is not sufficient to identify ATE_t or $ATE_t(m)$ in (4) either. To understand this limitation, it is useful to rewrite the conditional average treatment effect $ATE_t(m)$ in terms of the conditional treatment on the treated $ATT_t(m)$:

$$
\begin{aligned}
ATE_t(m|m) &= E(Y_t(1,m) - Y_t(0,m)|M=m) && (30)\\
&= E(Y_t(1,m) - Y_t(0,m)|M=m, D=1)P(D=1|M=m)\\
&\quad + E(Y_t(1,m) - Y_t(0,m)|M=m, D=0)P(D=0|M=m) && (31)\\
&= ATT_t(m|m)P(D=1|M=m)\\
&\quad + E(Y_t(1,m) - Y_t(0,m)|M=m, D=0)P(D=0|M=m). && (32)
\end{aligned}
$$

The Conditional Parallel Trends Assumption A.3 enable us to identify $ATT_t(m|m)$, but not $E(Y_t(1,m) - Y_t(0,m)|M = m, D = 0)$, which is the causal effect the treatment for the control group. Note that the control group never experience the treatment itself. Its identification requires an assumption that enable us to use the treatment group to evaluate the causal effect for the control group.

The lack of identification of average effects presented here is inline with the results in Callaway, Goodman-Bacon, and Sant'Anna (2021), who shows that the common trend assumption is not sufficient to identify causal effects of interest in the DiD design with a continuous treatment.

B.3 Common DiD Regression under Parallel Trend Assumptions

The TWFE regression in (2) is numerically equivalent to the following regression:[37]

$$\Delta Y_{it} = \alpha + \beta_{DiD} \cdot W_i + \epsilon_i, \text{ where } W_i = D_i \cdot M_i. \tag{33}$$

We seek to examines the causal content of the expected value of the OLS estimator for the parameter β_{DiD} in the regression above. To do so, consider the following notation. Let $\overline{M}_d = E(M|D = d); d \in \{1, 0\}$ be expected value of the moderator condition on the treatment group. Let $\overline{\Delta Y}_{td} = E(Y_t - Y_{t-1}|D = d); d \in \{1, 0\}$ denotes the expected value of the outcome time difference condition on the treatment groups. Finally, let $P_d = P(D = d); d \in \{0, 1\}$ denotes the probability of each treatment group. Under this notation, we can state the following theorem:

Theorem T.5. Under standard OLS assumptions, the expected value of the OLS estimator for moderator DiD parameter β_{DiD} in (33) is given by the following:

$$\beta_{DiD} = \frac{\text{Cov}(\Delta Y_t, M|D = 1) + \left(\overline{\Delta Y}_{t1} - \overline{\Delta Y}_{t0}\right) \cdot \overline{M}_1 \cdot P_0}{\text{Var}(M|D = 1) + \overline{M}_1^2 \cdot P_0} \tag{34}$$

Moreover, consider replacing the moderator M by a linear transformation $M^* = M - \overline{M}_1$. Then, under Assumptions A.1 and A.3, the expected value of the OLS estimator for β_{DiD} in (33) is given by the following:

$$\beta^*_{DiD} = \int \frac{\partial E(Y_t(1) - Y_{t-1}(0)|D = 1, M^* = m)}{\partial m} \omega(m)\, dm \tag{35}$$

$$\text{where } \omega(m) = \frac{E(M^*|M^* > m, D = 1)\left(1 - F_{M^*|D=1}(m)\right)}{\text{Var}(M|D = 1)}. \tag{36}$$

Proof. See Appendix C.5. □

[37] This is the linear regression of the outcome time-difference ΔY_t on a constant term α and the interaction between the treatment indicator D and the moderator variable M,; that is, $W = D \cdot M$. Standard OLS assumptions are that the observed data $(Y_{it}, Y_{it-1}, D_i, M_i)$ denote random variables that are independent and identically distributed (i.i.d.) across i and ϵ_i is an i.i.d. unobserved mean-zero exogenous error term that is statistically independent of D_i, M_i.

Equation (34) is a statistical result arising from applying the Frisch-Waugh-Lovell Theorem (1933; 1963).[38] Under a linear transformation of the moderator, β_{DiD} in (35) is a weighted average of the time difference of the counterfactual outcomes for the treatment group (33). [39]

The main assessment of Theorem T.5 is that the estimate for the parameter β_{DiD} in the regressions (2) or (33) cannot be easily described in terms of the marginal effects in (5).

Appendix C Mathematical Proofs

C.0 Proof of Proposition P.1

The proposition requires multiple applications of the formula for the integration by parts. Namely, let $h(x) : \mathbb{R} \to \mathbb{R}$ be an integrable function and $g(x) : \mathbb{R} \to \mathbb{R}$ be an a differentiable function, then the following equation holds:

$$\int_a^b \frac{\partial g(x)}{\partial x} h(x) dx = \Big[g(x)h(x) \Big]_a^b - \int_a^b g(x) \frac{\partial h(x)}{\partial x} dx \tag{37}$$

Note that the moderator M is a continuous random variable in $[\underline{m}, \overline{m}]$, and $ATE_t(m)$ is differentiable. Thereby $ATE_t(m) = E(Y_t(1,m) - Y_t(0,m)|M = m)$ is continuous in $[\underline{m}, \overline{m}]$. Moreover, we have that

$$ATE_t = \int_{\underline{m}}^{\overline{m}} ATE_t(m) f_M(m) dm,$$

where $f_M(m) > 0$ is the probability density of M and $F_M(m) = \int_{\underline{m}}^{m} f_M(m) dm = P(M \leq m)$ denotes the cumulative probability function of M such that $F_M(\underline{m}) = 0$ and $F_M(\overline{m}) = 1$.

Let m^* be any value in $[\underline{m}, \overline{m}]$. We first apply (37) to the integral $\int_{m^*}^{\overline{m}} MATE_t(m)\,(1 - F_M(m))\,dm$:

[38] This result can also be understood as an ANOVA decomposition that rewrites the OLS coefficient as a weighted average of the intra- and between-groups regression coefficients (see, for instance, Section 4.2 of Yitzhaki (2013)). If $M_i = 1$ for all $i \in \mathcal{I}$, then β_{DiD} in Eq. (34) yields the standard DiD estimator for the TWFE model, $\beta_{DiD} = \overline{\Delta Y_{t1}} - \overline{\Delta Y_{t0}}$.

[39] The weights $\omega(m)$ in (36) are a function of truncated expectation and the CDF of the moderator. These weights are always positive and sum to one.

$$
\begin{aligned}
&\int_{m^*}^{\overline{m}} MATE_t(m)\,(1-F_M(m))\,dm \\
&\quad = \int_{m^*}^{\overline{m}} \frac{\partial ATE_t(m)}{\partial m}\,(1-F_M(m))\,dm \\
&\quad = \Big[ATE_t(m)\,(1-F_M(m))\Big]_{m^*}^{\overline{m}} + \int_{m^*}^{\overline{m}} ATE_t(m) f_M(m) dm \\
&\quad = \Big(ATE_t(\overline{m}|\overline{m})\,(1-F_M(\overline{m}))\Big) - \Big(ATE_t(m^*)\,(1-F_M(m^*))\Big) + \int_{m^*}^{\overline{m}} ATE_t(m) f_M(m) dm, \\
&\quad = -\Big(ATE_t(m^*)\cdot(1-F_M(m^*))\Big) + \int_{m^*}^{\overline{m}} ATE_t(m) f_M(m) dm, \\
&\therefore \int_{m^*}^{\overline{m}} ATE_t(m) f_M(m) dm = \int_{m^*}^{\overline{m}} MATE_t(m)\,(1-F_M(m))\,dm + ATE_t(m^*)\cdot(1-F_M(m^*))\,, \qquad (38)
\end{aligned}
$$

where the first equality comes from the definition of $MATE_t(m)$. The second equality applies the integration by parts. The fourth equality is due to the fact that $F_M(\overline{m}) = 1$. The last equality simply rearranges the terms.

Next, we apply (37) to the integral $\int_{\underline{m}}^{m^*} MATE_t(m)\big(-F_M(m)\big)dm$:

$$
\begin{aligned}
&\int_{\underline{m}}^{m^*} MATE_t(m)\big(-F_M(m)\big)dm \\
&\quad = \int_{\underline{m}}^{m^*} \frac{\partial ATE_t(m)}{\partial m}\big(-F_M(m)\big)dm \\
&\quad = \Big[ATE_t(m)\,(-F_M(m))\Big]_{\underline{m}}^{m^*} + \int_{\underline{m}}^{m^*} ATE_t(m) f_M(m) dm \\
&\quad = \Big(ATE_t(m^*)\,(-F_M(m^*))\Big) - \Big(ATE_t(\underline{m}|\underline{m})\,(-F_M(\underline{m}))\Big) + \int_{\underline{m}}^{m^*} ATE_t(m) f_M(m) dm, \\
&\quad = \Big(ATE_t \cdot F_M(m^*)\Big) + \int_{\underline{m}}^{m^*} ATE_t(m) f_M(m) dm, \\
&\therefore \int_{\underline{m}}^{m^*} ATE_t(m) f_M(m) dm = \int_{\underline{m}}^{m^*} MATE_t(m)\big(-F_M(m)\big)dm - ATE_t(m^*)\cdot F_M(m^*), \qquad (39)
\end{aligned}
$$

where the first equality comes from the definition of $MATE_t(m)$. The second equality applies the integration by parts. The fourth equality is due to the fact that $F_M(\overline{m}) = 1$. The last equality simply rearranges the terms.

The final expression is obtained by summing equations (38) and (39). The sum of the left-hand side of these two equations give us the average treatment effect:

$$
\int_{\underline{m}}^{m^*} ATE_t(m) f_M(m) dm + \int_{m^*}^{\overline{m}} ATE_t(m) f_M(m) dm = \int_{\underline{m}}^{\overline{m}} ATE_t(m) f_M(m) dm = ATE_t. \qquad (40)
$$

The sum of the right-hand side of equations (38) and (39) give us the following expression:

$$\left(\int_{\underline{m}}^{m^*} MATE_t(m)\big(-F_M(m)\big)dm - ATE_t(m^*)\cdot F_M(m^*)\right)$$
$$+\left(\int_{m^*}^{\overline{m}} MATE_t(m)\,(1-F_M(m))\,dm + ATE_t(m^*)\cdot(1-F_M(m^*))\right) \tag{41}$$
$$= \int_{\underline{m}}^{\overline{m}} MATE_t(m)\cdot\Big(\mathbf{1}[m \geq m^*](1-F_M(m)) - \mathbf{1}[m \leq m^*]\cdot F_M(m)\Big)dm + ATE_t(m^*). \tag{42}$$

We can equate the left-hand in (40) with the right-hand side in (42) to obtain the desired expression:

$$ATE_t = \int_{\underline{m}}^{\overline{m}} MATE_t(m)\cdot\Big(\mathbf{1}[m \geq m^*](1-F_M(m)) - \mathbf{1}[m \leq m^*]\cdot F_M(m)\Big)dm + ATE_t(m^*).$$

C.1 Proof of Theorem T.1

The identification of $ATT_t(m)$ in (6) is obtained by the following equations:

$$\begin{aligned}
ATT_t(m) &= E[Y_t(1,m) - Y_t(0,m)|D=1, M=m],\\
&= E[Y_t(1,m) - Y_{t-1}(0,m)|D=1, M=m] - E[Y_t(0,m) - Y_{t-1}(0,m)|D=1, M=m],\\
&= E[Y_t(1,m) - Y_{t-1}(0,m)|D=1, M=m] - E[Y_t(0,m) - Y_{t-1}(0,m)|D=0, M=m],\\
&= E[\Delta Y_t|D=1, M=m] - E[\Delta Y_t|D=0, M=m],
\end{aligned}$$

where the first equality is due to the definition of $ATT_t(m)$ in (3). The second equality adds and subtracts $E[Y_{t-1}(0,m)|D=1, M=m]$. The third equality invokes the Conditional Parallel Trends Assumption **A.3**. The last equality is due to **A.1**. Namely, the expected value of $Y_t(1,m)$ and $Y_{t-1}(0,m)$ are observed when conditioning on $(D=1, M=m)$, and the expected value of $Y_t(0,m)$ and $Y_{t-1}(0,m)$ are observed when conditioning on $D=0, M=m$.

The identification equation for ATT_t in (7) stems from the following equations:

$$\begin{aligned}
ATT_t &= E[Y_t(1) - Y_t(0)|D=1],\\
&= \int_m E[Y_t(1) - Y_t(0)|D=1, M=m]dF_{M|D=1}(m),\\
&= \int_m E[Y_t(1,m) - Y_t(0,m)|D=1, M=m]dF_{M|D=1}(m),\\
&= \int_m E[Y_t(1,m) - Y_t(0,m)|D=1, M=m]\frac{P(D=1|M)}{P(D=1)}dF_M(m),
\end{aligned}$$

where the second equation is due to the law of iterated expectations. The third equation is due to **A.1** and the fourth equation is due to the Bayes theorem.

C.2 Proof of Theorem T.2

The identification of $ATE_t(m)$ in (8) is obtained by the following equations:

$$\begin{aligned} ATE_t(m) &= E[Y_t(1,m) - Y_t(0,m)|M=m], \\ &= E[Y_t(1,m) - Y_{t-1}(0,m)|M=m] - E[Y_t(0,m) - Y_{t-1}(0,m)|M=m], \\ &= E[Y_t(1,m) - Y_{t-1}(0,m)|D=1, M=m] - E[Y_t(0,m) - Y_{t-1}(0,m)|D=0, M=m], \\ &= E[\Delta Y_t|D=1, M=m] - E[\Delta Y_t|D=0, M=m], \end{aligned}$$

where the first equality is due to the definition of $ATE_t(m)$ in (3). The second equality adds and subtracts $E[Y_{t-1}(0,m)|M=m]$. The third equality invokes the Strong Parallel Trends **A.4** and the Full Support **A.2** . The last equality is due to **A.1**. Namely, the expected value of $Y_t(1,m)$ and $Y_{t-1}(0,m)$ are observed when conditioning on $(D=1, M=m)$, and the expected value of $Y_t(0,m)$ and $Y_{t-1}(0,m)$ are observed when conditioning on $D=0, M=m$.

The identification equation for ATE_t in (9) stems from the following equations:

$$\begin{aligned} ATE_t &= E[Y_t(1) - Y_t(0)], \\ &= \int_m E[Y_t(1) - Y_t(0)|M=m]dF_M(m), \\ &= \int_m E[Y_t(1,m) - Y_t(0,m)|D=1, M=m]dF_M(m), \end{aligned}$$

where the second equation is due to the law of iterated expectations and the third equation is due to **A.1**.

C.3 Proof of Theorem T.3

The DiD estimator for β_{DiD} in the TWFE regression (10) is numerically equivalent to the estimator obtained from the following regression:[40]

$$\Delta Y_{it} = \alpha + \gamma \cdot D_i + \kappa \cdot M_i + \beta_{DiD} \cdot W_i + \upsilon_i, \text{ such that } W_i = D_i \cdot M_i, \tag{43}$$

where $\Delta Y_{it} = Y_{it} - Y_{it-1}$ is the temporal outcome difference for unit i.

The first sampling weighting scheme of the theorem is uniform, which means that the regression employs the actual distribution of the data. Equation (11) is a standard result in the OLS literature. By using the full set of indicator interaction, the DiD estimator evaluates the difference of the OLS estimators if we were to regress two separate regressions, one for the control (untreated) group and another for the treatment group.

Equations (12)–(13) are based on the Yitzhaki's Weights (Yitzhaki 2013), which states that the covariance of any random variables Y, X such that $E(|Y|) < \infty$ and $E(|X|) = \mu_X < \infty$

[40]The following expression denotes the regression of the outcome time-difference ΔY_t on a constant term α, the treatment indicator D, the moderator M, and their interaction $W = D \cdot M$.

and $E(Y|X)$ is differentiable, can be expressed as:

$$\text{Cov}(Y, X) = \int_{-\infty}^{\infty} \frac{\partial E(Y|X = x)}{\partial x} \omega(x) dx,$$
$$\text{such that } \omega(x) = E(X - \mu_X | X > x)(1 - F_X(x)).$$

According to the equation above, we can express the covariances $\text{Cov}(\Delta Y_t, M|D = d); d \in \{0, 1\}$ by the following expression:

$$\text{Cov}(\Delta Y_t, M|D = d) = \int_{-\infty}^{\infty} \frac{\partial E(\Delta Y_t|D = d, M = m)}{\partial m} \omega(m) dm; \quad d \in \{0, 1\}, \tag{44}$$
$$\text{such that } \omega(m) = E(M - \overline{M}_d | M > m, D = d)(1 - F_{M|D=d}(m)),$$

where $\overline{M}_d \equiv E(M|D = d); d \in \{0, 1\}$.

The second weighting scheme sets the distribution of the moderator of the treatment and control group to the distribution of the treatment group. The DiD parameter of the regression still delivers the difference of two separate OLS regressions that evaluate the covariance between ΔY_t and M over the variance of M for each treatment group. The weighting scheme modifies the distribution of M. The first OLS parameter β_1 is associated with the treatment group ($D = 1$) and the asymptotic cumulative distribution of M is given by $F_{M|D=1}(m)$. The expected value of this OLS estimator is given by:

$$E(\beta_1) = \int_{-\infty}^{\infty} \frac{\partial E(\Delta Y_t|D = 1, M = m)}{\partial m} \omega_1(m) dm \tag{45}$$
$$\text{where } \omega_1(m) = \frac{E(M - E(M|D = 1)|M > m, D = 1)(1 - F_{M|D=1}(m))}{\text{Var}(M|D = 1)}. \tag{46}$$

The second OLS parameter β_0 is associated with the control group ($D = 0$) and the cumulative distribution of M is also given by $F_{M|D=1}(m)$. The expected value of this OLS estimator is given by:

$$E(\beta_0) = \int_{-\infty}^{\infty} \frac{\partial E(\Delta Y_t|D = 0, M = m)}{\partial m} \omega_1(m) dm, \tag{47}$$

where $\omega_1(m)$ is the same as in (46). The difference between the expected value of the OLS estimators in (53) and (47) is:

$$E(\beta_1) - E(\beta_0) = \int_{-\infty}^{\infty} \frac{\partial \left(E(\Delta Y_t|D = 1, M = m) - E(\Delta Y_t|D = 0, M = m)\right)}{\partial m} \omega_1(m) dm \tag{48}$$
$$= \int_{-\infty}^{\infty} MATT_t(m) \omega_1(m) dm, \tag{49}$$

where the second equality is due to **T.1**.

The last weighting scheme sets the conditional distribution of the moderator of the treatment and control groups to the unconditional distribution of the moderator. The DiD parameter of the regression also delivers the difference of two separate OLS regressions that evaluate the covariance between ΔY_t and M over the variance of M for each treatment group. However, the weighting scheme modifies the distribution of M. The first OLS parameter β_1^* is associated with the treatment group ($D = 1$) and the asymptotic cumulative distribution of M is given by $F_M(m)$. The expected value of this OLS estimator is given by:

$$E(\beta_1^*) = \int_{-\infty}^{\infty} \frac{\partial E(\Delta Y_t|D=1, M=m)}{\partial m}\omega^*(m)dm \tag{50}$$

$$\text{where } \omega^*(m) = \frac{E(M - E(M|D=1)|M>m, D=1)(1-F_{M|D=1}(m))}{\text{Var}(M|D=1)}. \tag{51}$$

The second OLS parameter β_0^* is associated with the control group ($D = 0$) and the cumulative distribution of M is also given by $F_M(m)$. The expected value of this OLS estimator is given by:

$$E(\beta_0^*) = \int_{-\infty}^{\infty} \frac{\partial E(\Delta Y_t|D=0, M=m)}{\partial m}\omega^*(m)dm, \tag{52}$$

where $\omega^*(m)$ is the same as in (51). The difference between the expected value of the two OLS estimators in (50) and (52) is:

$$E(\beta_1^*) - E(\beta_0^*) = \int_{-\infty}^{\infty} \frac{\partial \left(E(\Delta Y_t|D=1, M=m) - E(\Delta Y_t|D=0, M=m)\right)}{\partial m}\omega^*(m)dm \tag{53}$$

$$= \int_{-\infty}^{\infty} MATE_t(m)\omega^*(m)dm, \tag{54}$$

where the second equality is due to **T.2**.

C.4 Proof of Theorem T.4

The OLS estimator of the linear regression in (14) is numerically equivalent to the estimator of the regression (15), that is,

$$\Delta Y_{it} = \alpha + \beta_{DiD} \cdot M_i + (\epsilon_{it} - \epsilon_{it-1}). \tag{55}$$

It is useful to rewrite the dependent variable ΔY_{it} in the following manner:

$$\begin{aligned}
\Delta Y_{it} &\equiv Y_{it} - Y_{it-1} &(56)\\
&= Y_{it}(1) - Y_{it-1}(0) &(57)\\
&= \big(Y_{it}(1) - Y_{it}(0)\big) + \big(Y_{it}(0) - Y_{it-1}(0)\big) &(58)\\
&= \big(Y_{it}(1) - Y_{it}(0)\big) + \big((\tau_t - \tau_{t-1}) + (v_{it} - v_{it-1})\big) &(59)
\end{aligned}$$

Equation (56) simply uses the definition that ΔY_{it} is the outcome time difference. Equation (57) uses Assumption **A.1** and the fact that all units are treated, $D = 1$, thus, in period $t-1$, none of the units are treated, while in period t, all units are treated. Equation (58) adds and subtracts the term $Y_{it}(0)$. Equation (59) uses the assumption that the counterfactual outcome for the untreated units is given by $Y_{it}(0) = \kappa_i + \tau_t + f_0(M_i) + v_{it}$ for t and $t-1$. Thus, $Y_{it}(0) - Y_{it-1}(0) = (\tau_t - \tau_{t-1}) + (v_{it} - v_{it-1})$ as stated in (59).

The expected value of β_{DiD}-estimator is given by:

$$\begin{aligned}
\beta_{DiD} &= \frac{Cov\Big(\Delta Y_t, M\Big)}{Var(M)}, &(60)\\
&= \frac{Cov\Big(\big(Y_{it}(1) - Y_{it}(0)\big) + \big((\tau_t - \tau_{t-1}) + (v_{it} - v_{it-1}), M\big)\Big)}{Var(M)}, &(61)\\
&= \frac{Cov\Big(Y_{it}(1) - Y_{it}(0), M\Big)}{Var(M)}. &(62)
\end{aligned}$$

Equation (60) is due to independence the independence between error terms ϵ and M. Equation (61) replaces ΔY_t by the expression in (59). Equation (62) is due to the independence of employs the $(v_t - v_{t-1})$ and M and because $(\tau_t - \tau_{t-1})$ is a constant term.

We can now apply Yitzhaki's Weights (Yitzhaki 2013), who shows that the covariance of any random variables Y, X such that $E(|Y|) < \infty$ and $E(|X|) = \mu_X < \infty$ and $E(Y|X)$ is differentiable, can be expressed as:

$$\frac{\text{Cov}(Y,X)}{\text{Var}(X)} = \int_{-\infty}^{\infty} \frac{\partial E(Y|X=x)}{\partial x} \omega(x) dx, \tag{63}$$

$$\text{such that } \omega(x) = \frac{E(X - E(X)|X > x)(1 - F_X(x))}{\text{Var}(X)} \tag{64}$$

where the weighting function $\omega(x)$ is positive and integrate to one. Under the Full Support Assumption **A.2**, we can apply equation (63)–(64) to equation (62) in order to obtain the following expression:

$$\beta_{DiD} = \int \frac{\partial E(Y_t(1) - Y_t(0)|M = m, D = 1)}{\partial m} \frac{E(M - E(M))|M > m, B = 1)\left(1 - F_{M|D=1}(m)\right)}{\text{Var}(M|D = 1)} dm \tag{65}$$

$$= \int MATT_t(m) \frac{E(M - E(M))|M > m, D = 1)\left(1 - F_{M|D=1}(m)\right)}{\text{Var}(M|D = 1)} dm. \tag{66}$$

Equation (65) simply applies the Yitzhaki's Weights, while (66) uses the definition of $MATT_t$. The specification is conditioned on $D = 1$ because all agents belong to the treated group. This proof did not explicitly invoke the Conditional Parallel Trends (**A.3**) since the condition is implied by the linear equation that defines the counterfactual outcomes for the untreated.

The second part of the theorem assumes that the observed distribution of the moderator, $P(M = m|D = 1)$, is equal to the unconditional distribution $P(M = m)$. Moreover, the Strong Parallel Trend enable us to equate $MATT_t(m) = MATE_t(m)$. These two features enable us to express β_{DiD} in (66) as:

$$\beta_{DiD} = \int MATT_t(m) \frac{E(M - E(M))|M > m, D = 1)\left(1 - F_{M|D=1}(m)\right)}{\text{Var}(M|D = 1)} dm, \tag{67}$$

$$= \int MATE_t(m) \frac{E(M - E(M))|M > m)\,(1 - F_M(m))}{\text{Var}(M)} dm. \tag{68}$$

C.5 Proof of Theorem T.5

This proof adopts a short-hand notation. Let $\overline{M}_d = E(M|D = d); d =\in \{1, 0\}$ denotes the expected value of the moderator condition on the treatment group; Let $\overline{\Delta Y}_d = E(Y_t - Y_{t-1}|D = d); d =\in \{1, 0\}$ denotes the expected value of the outcome time difference condition on the treatment groups; Let $P_d = P(D = d); d \in \{0, 1\}$ denotes the probability of each treatment group; and $\overline{\Delta Y} = E(\Delta Y) = \overline{\Delta Y}_1 P_1 + \overline{\Delta Y}_0 P_0$.

The expected value of the OLS estimator of the parameter β_{DiD} in (33) evaluates the following ratio:

$$\beta_{DiD} + \frac{\mathrm{Cov}(\Delta Y_t, D \cdot M)}{\mathrm{Var}(D \cdot M)} \tag{69}$$

We can express the numerator of (69) as:

$$\begin{aligned}
\mathrm{Cov}(\Delta Y_t, D \cdot M) &= E((\Delta Y_t - \overline{\Delta Y}) \cdot M|D = 1)P_1 && (70)\\
&= E(\Delta Y_t \cdot M|D = 1)P_1 - \overline{\Delta Y} \cdot \overline{M}_1 P_1 && (71)\\
&= E(\Delta Y_t \cdot M|D = 1)P_1 - (\overline{\Delta Y}_1 P_1 + \overline{\Delta Y}_0 P_0)\overline{M}_1 P_1 && (72)\\
&= (E(\Delta Y_t \cdot M|D = 1) - \overline{\Delta Y}_1 P_1 \overline{M}_1 + \overline{\Delta Y}_0 P_0 \overline{M}_1)P_1 && (73)\\
&= (E(\Delta Y_t \cdot M|D = 1) - \overline{\Delta Y}_1 \overline{M}_1 + \overline{\Delta Y}_1 \overline{M}_1(1 - P_1) - \overline{\Delta Y}_0 P_0 \overline{M}_1)P_1 && (74)\\
&= (\mathrm{Cov}(\Delta Y_t, M|D = 1) + \overline{\Delta Y}_1 \overline{M}_1 P_0 - \overline{\Delta Y}_0 P_0 \overline{M}_1)P_1 && (75)\\
&= \mathrm{Cov}(\Delta Y_t, M|D = 1)P_1 + (\overline{\Delta Y}_1 - \overline{\Delta Y}_0)P_0 \overline{M}_1 P_1 && (76)\\
&= (\mathrm{Cov}(\Delta Y_t, M|D = 1) + (\overline{\Delta Y}_1 - \overline{\Delta Y}_0)P_0 \overline{M}_1)P_1 && (77)
\end{aligned}$$

We can express the denominator of (69) as:

$$\begin{aligned}
\mathrm{Var}(D \cdot M) &= E((M \cdot D - E(M \cdot D)) \cdot (M \cdot D)) && (78)\\
&= E((M \cdot D - \overline{M}_1 P_1) \cdot (M \cdot D)) && (79)\\
&= E((M - \overline{M}_1 P_1) \cdot M|D = 1)P_1 && (80)\\
&= (E(M^2|D = 1) - \overline{M}_1^2 P_1) \cdot P_1 && (81)\\
&= (E(M^2|D = 1) - \overline{M}_1^2 P_1 - \overline{M}_1^2 P_0 + \overline{M}_1^2 P_0) \cdot P_1 && (82)\\
&= ((E(M^2|D = 1) - \overline{M}_1^2) + \overline{M}_1^2 P_0) \cdot P_1 && (83)\\
&= (\mathrm{Var}(M|D = 1) + \overline{M}_1^2 P_0) \cdot P_1 && (84)
\end{aligned}$$

The ratio of (77) and (84) generates the following equation:

$$\frac{\mathrm{Cov}(\Delta Y_t, D \cdot M)}{\mathrm{Var}(D \cdot M)} = \; = \frac{\mathrm{Cov}(\Delta Y_t, M|D = 1) + (\overline{\Delta Y}_1 - \overline{\Delta Y}_0)P_0 \overline{M}_1}{\mathrm{Var}(M|D = 1) + \overline{M}_1^2 P_0} \tag{85}$$

If we set $\overline{M}_1 = 0$, then we have that:

$$\frac{\mathrm{Cov}(\Delta Y_t, D \cdot M)}{\mathrm{Var}(D \cdot M)} = \; = \frac{\mathrm{Cov}(\Delta Y_t, M|D = 1)}{\mathrm{Var}(M|D = 1)} \tag{86}$$

The next part of the theorem employs the Yitzhaki's Weights (Yitzhaki 2013). Using integration by parts, it is easy to show that the covariance of any random variables Y, X

such that $E(|Y|) < \infty$ and $E(|X|) = \mu_X < \infty$ and $E(Y|X)$ is differentiable, can be expressed as:

$$\text{Cov}(Y, X) = \int_{-\infty}^{\infty} \frac{\partial E(Y|X = x)}{\partial x} E(X - \mu_X|X > x)(1 - F_X(x))dx, \tag{87}$$

Moreover, we can apply (87) to express the variance of a random variable X as:

$$\text{Var}(X) \equiv \text{Cov}(X, X) = \int_{-\infty}^{\infty} E(X - \mu_X|X > x)(1 - F_X(x))dx. \tag{88}$$

Setting $\overline{M}_1 \equiv E(M|D = 1) = 0$, and applying the formula (87) to the OLS estimator in (85), we obtain:

$$\begin{aligned}
&\frac{\text{Cov}(\Delta Y_t, D \cdot M)}{\text{Var}(D \cdot M)} = \\
&= \int \frac{\partial E(\Delta Y_t|D = 1, M = m)}{\partial m} \frac{E(M|M > m, D = 1)\left(1 - F_{M|D=1}(m)\right)}{\text{Var}(M|D = 1)} dm \\
&= \int \frac{\partial E(Y_t(1) - Y_{t-1}(0)|D = 1, M = m)}{\partial m} \frac{E(M|M > m, D = 1)\left(1 - F_{M|D=1}(m)\right)}{\text{Var}(M|D = 1)} dm
\end{aligned}$$

Equation (88) and the feature that $\overline{M}_1 = 0$ assures that the weights in the equation above are always positive and integrate to one.

Appendix D Additional Tables

Table A1: Impact of PNTR on Adolescent Physical Health, Cognition and School Dropout Rates

	(1)	(2)	(3)
Panel A. Physical health index			
Post × NTR gap	0.030	0.065	0.066
	(0.065)	(0.077)	(0.076)
Observations	5976	5976	5976
Control mean	-0.00	-0.00	-0.00
Panel B. Cognitive function index			
Post × NTR gap	0.023	0.077	0.072
	(0.065)	(0.062)	(0.057)
Observations	4892	4892	4892
Control mean	0.19	0.19	0.19
Panel C. School dropout rate			
Post × NTR gap	-0.026	-0.017	-0.015
	(0.030)	(0.033)	(0.033)
Observations	5977	5977	5977
Control mean	0.26	0.26	0.26
Prefecture-of-birth fixed effects	Yes	Yes	Yes
Year-of-birth fixed effects	Yes	Yes	Yes
Prefecture-specific linear trend	Yes	Yes	Yes
Post × Other trade policies	Yes	Yes	Yes
Post × Initial prefecture characteristics		Yes	Yes
Individual characteristics			Yes

Notes: Data are from the 2016–2018 CFPS. This table reports results of the DiD regressions of mental health outcomes on the interaction of the prefecture-level NTR gap and a post-PNTR indicator. Regressions in column 1 control for prefecture of birth fixed effects, year of birth fix effects, prefecture-specific linear trend in year of birth, and the post-PNTR indicator interacted with other trade policies including China's output, input and external tariffs, NTR rates, MFA quotas, and contract intensity. Regressions in column 2 further control for the post-PNTR indicator interacted with initial prefecture characteristics including GDP per capita, average population age, average population years of schooling, total number of children, and fertility rate. Regressions in column 3 further control for individual characteristics including age, gender, father's and mother's age, and indicator variables for whether the mother and father completed middle school. Standard errors are clustered at the prefecture of birth level. ***, **, and * denote significance at the 1, 5, and 10 percent levels.

Table A2: Robustness Checks: Alternative Measures of the NTR Gap

	Any depression (1)	Severe depression (2)
Panel A. NTR gap measured by excluding industries with the highest NTR gap		
Post × NTR gap	0.003	-0.043***
	(0.030)	(0.016)
Observations	14521	14521
Control mean	0.28	0.09
Panel B. NTR gap measured by excluding industries with the lowest NTR gap		
Post × NTR gap	0.002	-0.044**
	(0.037)	(0.021)
Observations	14521	14521
Control mean	0.28	0.09
Panel C. NTR gap winsorized at the 5/95 percentiles		
Post × NTR gap	0.002	-0.047**
	(0.035)	(0.019)
Observations	14521	14521
Control mean	0.28	0.09
Panel D. NTR gap measured by excluding nontradable industries		
Post × NTR gap	0.021	-0.096**
	(0.075)	(0.043)
Observations	14521	14521
Control mean	0.28	0.09
Prefecture-of-birth fixed effects	Yes	Yes
Year-of-birth fixed effects	Yes	Yes
Prefecture-specific linear trend	Yes	Yes
Post × Other trade policies	Yes	Yes
Post × Initial prefecture characteristics	Yes	Yes
Individual characteristics	Yes	Yes

Notes: Data are from the 2016–2018 CFPS. This table reports results of the DiD regressions of mental health outcomes on the interaction of the prefecture-level NTR gap and a post-PNTR indicator. Regressions control for prefecture of birth fixed effects, year of birth fix effects, prefecture-specific linear trend in year of birth, and the post-PNTR indicator interacted with other trade policies including China's output, input and external tariffs, NTR rates, MFA quotas, and contract intensity, the post-PNTR indicator interacted with initial prefecture characteristics including GDP per capita, average population age, average population years of schooling, total number of children, and fertility rate, and individual characteristics including age, gender, father's and mother's age, and indicator variables for whether the mother and father completed middle school. The knitwear industry has the highest NTR gap value and is excluded in Panel A. The water resources management industry, coal mining and washing industry, mineral mining and processing industry, and coking industry have the lowest NTR gaps and are excluded in Panel B. Standard errors are clustered at the prefecture of birth level. ***, **, and * denote significance at the 1, 5, and 10 percent levels.

Table A3: Robustness Checks: Alternative Specifications

	Any depression (1)	Severe depression (2)
Panel A. Regression weighted by the 1990 prefecture population		
Post $\times$ NTR gap	-0.020	-0.050**
	(0.031)	(0.020)
Observations	5978	5978
Control mean	0.17	0.07
Prefecture-of-birth fixed effects	Yes	Yes
Year-of-birth fixed effects	Yes	Yes
Prefecture-specific linear trend	Yes	Yes
Post $\times$ Other trade policies	Yes	Yes
Post $\times$ Initial prefecture characteristics	Yes	Yes
Individual characteristics	Yes	Yes
Panel B. Using year of birth fixed effects interacted with controls		
Post $\times$ NTR gap	-0.011	-0.056***
	(0.033)	(0.019)
Observations	14521	14521
Control mean	0.28	0.09
Prefecture-of-birth fixed effects	Yes	Yes
Year-of-birth fixed effects	Yes	Yes
Prefecture-specific linear trend	Yes	Yes
Year-of-birth fixed effects $\times$ Other trade policies	Yes	Yes
Year-of-birth fixed effects $\times$ Initial prefecture characteristics	Yes	Yes
Individual characteristics	Yes	Yes

Notes: Data are from the 2016–2018 CFPS. This table reports results of the DiD regressions of mental health outcomes on the interaction of the prefecture-level NTR gap and a post-PNTR indicator. Regressions control for prefecture of birth fixed effects, year of birth fix effects, prefecture-specific linear trend in year of birth, and the post-PNTR indicator interacted with other trade policies including China's output, input and external tariffs, NTR rates, MFA quotas, and contract intensity, the post-PNTR indicator interacted with initial prefecture characteristics including GDP per capita, average population age, average population years of schooling, total number of children, and fertility rate, and individual characteristics including age, gender, father's and mother's age, and indicator variables for whether the mother and father completed middle school. Regressions in Panel A are weighted by the 1990 prefecture population. Regressions in Panel B use year of birth fixed effects interacted with other trade policies and initial prefecture characteristics. Standard errors are clustered at the prefecture of birth level. ***, **, and * denote significance at the 1, 5, and 10 percent levels.

Table A4: Heterogeneous Effects of PNTR on Adolescent Mental Health Outcomes

	Any depression (1)	Severe depression (2)
Panel A. Interact with "Female"		
Post × NTR gap	0.032	-0.019
	(0.045)	(0.028)
Post × NTR gap × Interaction	-0.072	-0.053
	(0.049)	(0.040)
Observations	14521	14521
Control mean	0.28	0.09
Panel B. Interact with "Mother completed middle school"		
Post × NTR gap	0.062	-0.040*
	(0.055)	(0.022)
Post × NTR gap × Interaction	-0.070	-0.000
	(0.067)	(0.039)
Observations	14520	14520
Control mean	0.28	0.09
Panel C. Interact with "Parental absence for at least one week from ages 0-3"		
Post × NTR gap	0.004	-0.031
	(0.030)	(0.021)
Post × NTR gap × Interaction	-0.000	-0.098
	(0.182)	(0.103)
Observations	11245	11245
Control mean	0.27	0.09
Panel D: Interact with "Above the median initial share of the rural population"		
Post × NTR gap	0.036	-0.042**
	(0.042)	(0.020)
Post × NTR gap × Interaction	-0.028	0.065
	(0.163)	(0.110)
Observations	14521	14521
Control mean	0.28	0.09
Prefecture-of-birth fixed effects	Yes	Yes
Year-of-birth fixed effects	Yes	Yes
Prefecture-specific linear trend	Yes	Yes
Post × Other trade policies	Yes	Yes
Post × Initial prefecture characteristics	Yes	Yes
Individual characteristics	Yes	Yes

Notes: Data are from the 2016–2018 CFPS. This table reports results of the DiD regressions of mental health outcomes on the interaction of the prefecture-level NTR gap and a post-PNTR indicator and a triple interaction of that term with a female indicator in Panel A, with an indicator for whether the mother completed middle school in Panel B, an indicator of parental absence for at least one week from ages 0-3 in Panel C, and an indicator of whether the initial share of the rural population is above the median in Panel D. All regressions control for prefecture of birth fixed effects, year of birth fixed effects, prefecture-specific linear trend in year of birth, and the post-PNTR indicator interacted with other trade policies including China's output, input and external tariffs, NTR rates, MFA quotas, and contract intensity, the post-PNTR indicator interacted with initial prefecture characteristics including GDP per capita, average population age, average population years of schooling, total number of children, and fertility rate, and individual characteristics including age, gender, father's and mother's age, and indicator variables for whether the mother and father completed middle school. The regressions also control for the triple interactions of those terms with a heterogeneous group indicator. Standard errors are clustered at the prefecture of birth level. ***, **, and * denote significance at the 1, 5, and 10 percent levels.

Table A5: Impact of PNTR on Individual Migration Experience

	(1)	(2)	(3)
Panel A. Cross-prefecture migration since birth			
Post × NTR gap	0.006	0.005	0.005
	(0.011)	(0.011)	(0.011)
Observations	13100	13100	13100
Control mean	0.02	0.02	0.02
Panel B. Cross-prefecture migration since age 12			
Post × NTR gap	0.008	0.004	0.003
	(0.011)	(0.011)	(0.011)
Observations	9043	9043	9043
Control mean	0.02	0.02	0.02
Panel C. Rural-urban migration since age 12			
Post × NTR gap	0.021	0.022	0.024
	(0.025)	(0.026)	(0.026)
Observations	11697	11697	11697
Control mean	0.10	0.10	0.10
Prefecture-of-birth fixed effects	Yes	Yes	Yes
Year-of-birth fixed effects	Yes	Yes	Yes
Prefecture-specific linear trend	Yes	Yes	Yes
Post × Other trade policies	Yes	Yes	Yes
Post × Initial prefecture characteristics		Yes	Yes
Individual characteristics			Yes

Notes: Data are from the 2016–2018 CFPS. This table reports results of the DiD regressions of migration indicators on the interaction of the prefecture-level NTR gap and a post-PNTR indicator. Regressions in column 1 control for prefecture of birth fixed effects, year of birth fix effects, prefecture-specific linear trend in year of birth, and the post-PNTR indicator interacted with other trade policies including China's output, input and external tariffs, NTR rates, MFA quotas, and contract intensity. Regressions in column 2 further control for the post-PNTR indicator interacted with initial prefecture characteristics including GDP per capita, average population age, average population years of schooling, total number of children, and fertility rate. Regressions in column 3 further control for individual characteristics including age, gender, father's and mother's age, and indicator variables for whether the mother and father completed middle school. Standard errors are clustered at the prefecture of birth level. ***, **, and * denote significance at the 1, 5, and 10 percent levels.

Table A6: Impact of PNTR on Immigration and Emigration Rate

	Total population (1)	Male (2)	Female (3)
Panel A. Immigration rate in destination prefecture			
Post × NTR gap	0.070	-0.001	0.004
	(0.044)	(0.007)	(0.003)
Observations	1312	1312	1312
Control mean	0.05	0.02	0.01
Panel B. Emigration rate from origin prefecture			
Post × NTR gap	0.023	0.014	0.009
	(0.019)	(0.011)	(0.008)
Observations	1312	1312	1312
Control mean	0.04	0.02	0.02
Prefecture fixed effects	Yes	Yes	Yes
Survey year fixed effects	Yes	Yes	Yes
Prefecture-specific linear trend	Yes	Yes	Yes
Post × Other trade policies	Yes	Yes	Yes
Post × Initial prefecture characteristics	Yes	Yes	Yes

Notes: Data are from the 2000 (the earliest census year where migration data are available), 2005, 2010, and 2015 population censuses in China. This table reports results of the DiD regressions of migration outcomes (immigration and emigration rates) on the interaction of the prefecture-level NTR gap and a post-PNTR indicator. Migration is defined as migrants aged 20-45 who moved across prefectures to seek jobs. The immigration rate is measured as the ratio of migrants who arrived in a given destination prefecture to the total number of non-migrant residents in that prefecture. The emigration rate is measured as the share of migrants who left a given prefecture to the total number of residents in that prefecture. All regressions control for prefecture fixed effects, survey year fixed effects, prefecture-specific linear trend, the post-PNTR indicator interacted with other trade policies including China's output, input and external tariffs, NTR rates, MFA quotas, and contract intensity, and the post-PNTR indicator interacted with initial prefecture characteristics including GDP per capita, average population age, average population years of schooling, total number of children, and fertility rate. Standard errors are clustered at the prefecture level. ***, **, and * denote significance at the 1, 5, and 10 percent levels.

Table A7: Impact of PNTR on Parental Absence

	(1)	(2)	(3)
Panel A. Parents were absent for at least one week from ages 0-3			
Post × NTR gap	-0.024	-0.007	-0.006
	(0.029)	(0.033)	(0.032)
Observations	11253	11253	11253
Control mean	0.10	0.10	0.10
Prefecture-of-birth fixed effects	Yes	Yes	Yes
Year-of-birth fixed effects	Yes	Yes	Yes
Prefecture-specific linear trend	Yes	Yes	Yes
Post × Other trade policies	Yes	Yes	Yes
Post × Initial prefecture characteristics		Yes	Yes
Individual characteristics			Yes
Panel B. A parent was not living in the household and seeking employment elsewhere			
Panel B1. Mother			
Post × NTR gap	0.044	0.021	0.021
	(0.040)	(0.044)	(0.045)
Observations	3446	3446	3446
Control mean	0.01	0.01	0.01
Panel B2. Father			
Post × NTR gap	0.000	0.029	0.024
	(0.063)	(0.079)	(0.079)
Observations	3446	3446	3446
Control mean	0.03	0.03	0.03
Prefecture fixed effects	Yes	Yes	Yes
Survey year fixed effects	Yes	Yes	Yes
Prefecture-specific linear trend	Yes	Yes	Yes
Post × Other trade policies	Yes	Yes	Yes
Post × Initial prefecture characteristics		Yes	Yes
Individual characteristics			Yes

Notes: Data in Panel A are from the 2016–2018 CFPS and data in Panel B are from the 1993-2015 CHNS. Regression in column 1 controls for prefecture of birth fixed effects (prefecture fixed effects in Panel B), year of birth fixed effects (survey year fixed effects in Panel B), prefecture-specific linear time trend, and the post-PNTR indicator interacted with other trade policies including China's output, input and external tariffs, NTR rates, MFA quotas, and contract intensity. Regression in column 2 further controls for the post-PNTR indicator interacted with initial prefecture characteristics including GDP per capita, average population age, average population years of schooling, total number of children, and fertility rate. Regression in column 3 further controls for individual characteristics including age, gender, father's and mother's age, and indicator variables for whether the mother and father completed middle school. Standard errors are clustered at the prefecture of birth level in Panel A and are clustered at the prefecture level in Panel B. ***, **, and * denote significance at the 1, 5, and 10 percent levels.

Table A8: Impact of PNTR on Fertility Outcomes

	Births per 1,000 women (1)	Number of children (2)	Percent of women with children (3)
Post × NTR gap	2.761	-613.377	-0.011
	(2.054)	(381.649)	(0.010)
Observations	1640	1640	1640
Control mean	46.71	6799.82	0.82
Prefecture fixed effects	Yes	Yes	Yes
Survey year fixed effects	Yes	Yes	Yes
Prefecture-specific linear trend	Yes	Yes	Yes
Post × Other trade policies	Yes	Yes	Yes
Post × Initial prefecture characteristics	Yes	Yes	Yes

Notes: Data are from the 1990, 2000, 2005, 2010, and 2015 population censuses in China. This table reports results of the DiD regressions of fertility outcomes on the interaction of the prefecture-level NTR gap and a post-PNTR indicator. All regressions control for prefecture fixed effects, year fixed effects, and the post-PNTR indicator interacted with other trade policies including China's output, input and external tariffs, NTR rates, MFA quotas, and contract intensity. The regressions also control for the post-PNTR indicator interacted with initial prefecture characteristics including GDP per capita, average population age, average population years of schooling, total number of children, and fertility rate. Standard errors are clustered at the prefecture level. ***, **, and * denote significance at the 1, 5, and 10 percent levels.