Online Supplement for "Currency Pegs, Trade Deficits and Unemployment: A Reevaluation of the China Shock"

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A Alternative Theoretical Models

A.1 Quantity-side friction

In this section, I explore a model analogous to the stylized model in Section 2.3, except with one difference: *nominal* rigidity is replaced with *quantity* rigidity. We explore the model implications, most notably how the propositions change.

Setup and equilibrium. The model setup is identical to Section 2.3, so I skip the details. The main difference is that we replace wage rigidity ($\{w_{i0}\}$ is exogenously given) with quantity rigidity, such that $\{L_{i0}\}$ is exogenous and given by the pre-shock steady-state equilibrium value. Since there is no nominal rigidity, the *absolute level* of nominal variables and the nominal exchange rate play no role in the equilibrium. Thus we normalize the exchange rate to $e_t = 1$.

The laissez-faire (no tariffs) equilibrium conditions are given by

$$P_{jt} = (\sum_i (P_{ijt})^{1-\sigma})^{1/(1-\sigma)}, \tag{A.1}$$

$$\lambda_{ijt} = \frac{(P_{ijt})^{1-\sigma}}{\sum_l P_{ljt}^{1-\sigma}}, \tag{A.2}$$

$$u'(C_{jt}) = \beta(1+i_{jt})\frac{P_{jt}}{P_{jt+1}}u'(C_{jt+1}) = \beta R_{jt} u'(C_{jt+1}), \tag{A.3}$$

$$\frac{1+i_{F1}}{1+i_{H1}} = \frac{e_1}{e_0}, \tag{A.4}$$

$$v'(L_{j1}) = \frac{u'(C_{j1})w_{j1}}{P_{j1}} \tag{A.5}$$

$$P_{ijt} = \frac{w_{it}}{A_{ij}} \tag{A.6}$$

$$L_{it} = \sum_j \frac{C_{ijt}}{A_{ij}} \tag{A.7}$$

$$w_{i0}L_{i0} + \frac{w_{i1}L_{i1}}{1+i_i} = P_{i0}C_{i0} + \frac{P_{i1}C_{i1}}{1+i_i} \tag{A.8}$$

with an exogenous $\{L_{i0}\}$ set at the steady-state values under the pre-shock $\{A_{ij}\}$ at $t = -1$.

First, since there is no nominal rigidity, we have monetary neutrality; this is a *real* economy where nominal values only play a unit of account role. Thus we may normalize Home relative wage to 1 in both periods, and the exchange rate $e_0 = e_1 = 1$ in both periods. Thus what matters is the relative wage of Foreign in each period.

We first make the following assumption about the *flexible-quantity* equilibrium:

Assumption 1. *If we denote $L_i^*(\{A_{ij}\})$ the labor supply under a static, flexible-quantity economy* *under productivity* $\{A_{ij}\}$, *we have*

$$L_H^*(\{A_{ij,0}\}) < L_H^*(\{A_{ij,-1}\}) \quad \text{and } L_F^*(\{A_{ij,0}\}) < L_F^*(\{A_{ij,-1}\})$$

The assumption states that in response to Foreign productivity growth, Home workers would want to supply less labor, whereas Foreign workers would want to supply more labor. At Home, this would hold because import prices decline, real wage goes up, so both the income effect and substitution effect work towards less labor supply. At Foreign, a productivity growth would imply more labor supply iff the Frisch elasticity is large (so labor supply responds more to higher income). Alternatively, any multi-sector model with a sectoral shock (labor moves into this sector in China, and moves out in the US) would generate this direction.

Thus, the *quantity rigidity* on short-run labor $\{L_{H0}, L_{F0}\}$ (which could be motivated by search friction a la Mortensen and Pissarides (1994), or sectoral reallocation a la Artuç et al. (2010)) is such that Home wants to supply less labor but cannot, and Foreign wants to supply more labor but cannot.[1] Under this framework, we have the following properties:

Proposition A.1. *Under the above quantity rigidity framework, we have:*

(a) $\omega_0 < \omega_1$*: Home relative wage is lower in the short-run than the long-run.*

(b) $B_{H1} > 0$*: Home saves in the short-run.*

(c) $\mu_{H0} < 0$*: there is overheating at Home in the short-run.*

Proof. (Sketch of proof)

The first part follows from our assumption: since L_H under flexible quantity would have been lower, we have $L_{H0} > L_{H1}$ and $L_{F0} < L_{F1}$. Since this pins down total goods supply, for the goods market to clear in each period we must have $\omega_0 < \omega_1$.

The second part's proof is analogous to the proof of Proposition 2 in the Appendix of the main text. Given $\omega_0 < \omega_1$, we can rearrange the terms to get a sufficient condition based on expenditure switching and relative inflation; with $\sigma > \gamma$, we get $B_{H1} > 0$.

The proof of the third part is a combination of two facts:

- Short-run Home relative wage is lower in the short-run than the flexible-quantity level ($\omega_0 < \omega^{flex}$, follows from the fixed labor supply)
- Short-run Home labor is higher than in the flexible-quantity level ($L_0 > L^{flex}$)
- Home's consumption C_{H0} is pinned down by relative wage ω_0 and the labor supply L_{H0}, L_{F0} (by solving the system of equations governing labor supply).

[1] This is the dynamics in Dix-Carneiro et al. (2023).

Analogously to Proposition 2 of the main text, we can verify that the desired labor supply is larger than the flexible-quantity labor supply, which in turn is greater than the labor demanded at $t = 0$. $\square$

The above proposition highlights the differential predictions of quantity rigidity models and nominal rigidity models. In response to a permanent Foreign growth, if the source of labor friction is on nominal wages, Proposition 2 of the main text shows that Home's relative wage is *higher* in the short-run, Home runs a trade *deficit*, and Home faces *unemployment*. On the other hand, if the source of labor friction is on quantity, Proposition A.1 shows that Home's relative wage is *lower* in the short-run, Home runs a trade *surplus*, and Home faces *overheating*. (Indeed, in the quantity rigidity model of Dix-Carneiro et al. (2023), we find that the US borrows in response to Chinese growth.)

The stylized facts of the 2000s (Figure 1 of the main text) are consistent with the wage rigidity model as opposed to the quantity rigidity model. This provides supporting evidence that, in analyzing the labor market response to the China shock, an important channel is nominal rigidity that generates involuntary unemployment in the US.

B Data and Calibration

This Appendix builds on Section 3.1 and describes the construction of our data and our calibration strategy.

B.1 WIOD data

Our main source of trade data is the World Input-Output Database (WIOD) 2016 release Timmer et al. (2015). The World Input-Output Table in the WIOD cover 44 countries and a rest-of-world aggregate, and the data spans from 2000 to 2014.

List of country aggregates and sectors. We follow Dix-Carneiro et al. (2023) and divide the world into six country aggregates and six sectors, focusing on US (country 1) and China (Country 2). Table 1 shows our country aggregates, and Table 2 shows how the 56 sectors in the WIOD are mapped to the six broad sectors considered in our model.

	Group	Countries in group
1	USA	USA
2	China	China
3	Europe	Austria (AUT), Belgium (BEL), Bulgaria (BGR), Switzerland (CHE), Cyprus (CYP), Czech Republic (CZE), Germany (DEU), Denmark (DNK), Spain (ESP), Estonia (EST), Finland (FIN), France (FRA), United Kingdom (GBR), Greece (GRC), Croatia (HRV), Hungary (HUN), Ireland (IRL), Italy (ITA), Lithuania (LTU), Luxembourg (LUX), Latvia (LVA), Malta (MLT), Netherlands (NLD), Norway (NOR), Poland (POL), Portugal (PRT), Romania (ROU), Slovakia (SVK), Slovenia (SVN), Sweden (SWE)
4	Asia/Oceania	Australia (AUS), Japan (JPN), Korea (KOR), Taiwan (TWN)
5	Americas	Brazil (BRA), Canada (CAN), Mexico (MEX)
6	Rest of World	Indonesia (IDN), India (IND), Russia (RUS), Turkey (TUR), ROW

Table B.1: Country definitions

	Sector aggregate	WIOD sector
1	Agriculture and Mining	Agriculture (1-3), Mining (4)
2	LT Manufacturing	Wood (7), Paper and Printing (8-9), Coke and Petroleum (10), Basic and Fabricated Metals (15-16), other mfg (22)
3	MT Manufacturing	Food (5), Textiles (6), Rubber (13), Mineral (14)
4	HT Manufacturing	Chemical and Pharmaceutical (11-12), Machinery, Computers and Motor Vehicles (17-23)
5	LT Services	Utilities (24-26), Construction (27), Wholesale and Retail (28-30), Transportation (31-35), Accommodation (36), Other Service (54), Household (55), Miscellaneous (56)
6	HT Services	Media and Telecommunications (37-39), IT (40), Finance (41-43), Real Estate (44), Legal (45), Architecture (46), Science (47), Advertising (48), Other Professional (49), Government and Education (50-52), Health (53)

Table B.2: Sector definitions

Note: The numbers inside parentheses denote the WIOD sectors, which follow the International Standard Industrial Classification revision 4 (ISIC Rev. 4). The classification of the six broad sectors follow Dix-Carneiro et al. (2023). In the sector aggregate classifications, (L,M,H) stand for Low-, Medium-, High- and T stands for Technology.

B.1.1 Constructed variables

The World Input-Output Table of WIOD contains the following raw data:

- M_{ijt}^{sn}, goods produced in sector s at country i that is used as inputs for goods in sector n at country j.
- F_{ijt}^{s}, goods produced in sector s at country i that is used as final expenditure in country j. (There are five expenditure categories; three consumption and two investment. We aggregate them.)
- GO_{it}^{s}, VA_{it}^{s}, ITM_{it}^{s} denote gross output, value added and international transport margins in country, sector (i,s) respectively.

Since the data comprises 44 countries and 56 sectors, we map this into our 6-sector, 6-country model by a direct sum.

From M_{ijt}^{sn} and F_{ijt}^{s}, we obtain the following:

- X_{ijt}^{s}, the total exports from i to j in sector s, given by

$$X_{ijt}^{s} = F_{ijt}^{s} + \sum_{n} M_{ijt}^{sn}$$

- λ^s_{ijt}, the share of sector s expenditure in j that originates from i, given by

$$\lambda^s_{ijt} = \frac{X^s_{ijt}}{\sum_{i'} X^s_{i'jt}}$$

- IO^{sn}_{it}, the input-output table of country i, given by

$$IO^{sn}_{it} = \sum_{i'} M^{sn}_{i'it}$$

- E^s_{it}, expenditure of country i in sector s, by

$$E^s_{it} = \sum_{s} F^s_{i'it}$$

We also obtain the net exports of country i by

$$NX_{it} = \sum_s VA^s_{it} + \sum_s ITM^s_{it} - \sum_s C^s_{it}$$

To ensure that net exports sum to zero, we assign any error to the rest-of-world.

From the WIOD Socio-Economic Accounts (SEA), we obtain the following:

- Industry-level employment $L^s_{i,2000}$ at period $t = 0$: we use the 2000 values as the initial condition for our model.
- Sectoral prices. We obtain $P^{s,dom}_{it}$, the domestic output price (price deflator) of country i in WIOD sector j expressed in millions of dollars. We closely follow the procedure in Dix-Carneiro et al. (2023) to construct $P^{s,dom}_{it}$ for our 6 country aggregates i and 6 sectors j.

We use the constructed $\{X^s_{ijt}, \lambda^s_{ijt}, IO^{sn}_{it}, E^s_{it}, NX_{it}, VA_{it}, GO_{it}, L^s_{i,2000}, P^{s,dom}_{it}\}$ in our calibration.

B.2 CPS data

To construct labor transition across sectors, we use the Current Population Survey (CPS). We rely on the annual retrospective questions from the Annual Social and Economics Supplement (ASEC) of the CPS. We map the 1990 Census industry codes in the CPS to the WIOD sector codes (based on ISIC Rev. 4) then into our 6 sectors, and obtain the transition ratio of employment from sector s to sector n at time t:

$$\mu^{sn}_t = \frac{1_{s,t-1} 1_{nt} wt_{it}}{\sum_{s'} 1_{s,t-1} 1_{s't} wt_{it}}$$

B.3 Calibration of parameters outside of the model

The parameters in Panel A of Table 1 are calibrated outside the model. We make note of two parameters important in our model, which are σ (Armington elasticity) and κ (slope of the New Keynesian Phillips Curve with respect to the output gap).

Calibration of σ. We use $\sigma = 5$ as the elasticity of within-sector goods substitution across different origins. This is identical to the elasticity used in Rodríguez-Clare et al. (2022), and generates the same gravity trade equation as in Dix-Carneiro et al. (2023)[2]. In Appendix E, we assess the sensitivity of our results to different levels of the elasticity. As long as the elasticity is greater than 1, our results are qualitatively identical, as we show in Section 2.3.

Calibration of κ. Hazell et al. (2022) estimate the slope of the following equation for unemployment:

$$\pi_t = -\kappa' \hat{u}_t + \beta E_t \pi_{t+1} + \nu_t$$

where $\hat{u}_t = \bar{u}_t - u_t$ is the gap from full employment, and using inter-state panel data, at a quarterly frequency, and find $\kappa' = 0.0062$. In our context, our time is annual, so the equivalent form is

$$\pi_t = -\kappa'(1 + \beta^{1/4} + \beta^{2/4} + \beta^{3/4})\hat{u}_t + \beta E_t \pi_{t+1}.$$

Moreover, their measure of unemployment is $u_t = 1 - N_{Ht}$. In our context, our wage NKPC is given by

$$\log(1 + \pi_t^w) = \kappa(v'(\ell_t) - \frac{w_t}{P_t} u'(C_t)) + \beta \log(1 + \pi_{t+1}^w)$$

The output gap can be rewritten as $v'(\ell_t) - \frac{w_t}{P_t} u'(C_t) = v'(\ell_t) - v'(\ell_t^D)$ where ℓ_t^D is the desired labor supply at this level. Linearizing v near the full-employment level $\ell_t = 1$, we have

$$\pi_t^w = \kappa \frac{\theta}{\varphi}(\ell_t - 1) + \beta \pi_{t+1}^w$$

Lastly, if wages increase by $X\%$ everywhere, the price index would also increase proportionately because production technology has constant returns to scale. Thus, the κ value consistent with Hazell et al. (2022) is given by

$$\kappa = \varphi \kappa' \frac{1}{\theta}(1 + \beta^{1/4} + \beta^{2/4} + \beta^{3/4}) = 0.05$$

using our values of $\varphi = 1.0, \beta = 0.95$, and the population average of θ given by 0.966.

[2] The formulation is different, because Dix-Carneiro et al. (2023) use a Eaton-Kortum model of perfect competition with a continuum of goods. In our model, the gravity equation is governed by a scale of $(1 - \sigma)$, whereas in their model it is governed by $-\lambda$ where λ is the Frechet scale parameter. Dix-Carneiro et al. (2023) use $\lambda = 4$, generating the same gravity equation.

B.4 Calibration of parameters in our model

The next paragraphs detail the calibration of parameters in Panel B of Table 1, using the WIOD and CPS data above. In this section, a variable with a bar above ($\overline{X}$) denotes variables directly observable in the data, and all other variables denote equilibirum objects.

We first note that the preference shares and production function parameters are directly measurable from the data:

$$\alpha_{it}^{s} = \frac{\overline{E}_{it}^{s}}{\sum_n \overline{E}_{it}^{n}} \tag{B.1}$$

$$\phi_{it}^{sn} = \frac{\overline{IO}_{it}^{sn}}{\sum_{s'} \overline{IO}_{it}^{s'n}} \tag{B.2}$$

$$\phi_{it}^{s} = \frac{\overline{VA}_{it}^{s}}{\overline{GO}_{it}^{s}} \tag{B.3}$$

The calibration of the remaining parameters $\tau_{ijt}^{s}, A_{it}^{s}, \delta_{it}^{s}, \eta_{it}^{s}, \chi_{it}^{sn}$ requires use of our model. We first calibrate the 2000 values, and then calibrate the 'shocks' to these variables.

B.4.1 Calibration of the initial period

Since δ_{it}^{s} govern intertemporal preference shocks, we need not calibrate it for the year 2000. We assume that the model is in steady-state in the year 2000, which implies two assumptions: the first is that the labor market is in full employment (no output gap), and that the labor distribution L_i^s in 2000 is the steady-state distribution of labor under the assumption that parameters $\{\tau_{ijt}^{s}, A_{it}^{s}, \eta_{it}^{s}, \chi_{it}^{sn}, \theta_{it}^{s}\}$ do not change from 2000 values. This simplifies our analysis without hurting the 'effect of the China shock.'

Suppressing the time subscripts t, we calibrate the 2000 values of $\{\tau_{ij}^{s}, A_i^s, \eta_i^s, \chi_i^{sn}, \theta_i^s\}$ to match the following observed data:

- Trade cost τ_{ij}^{s} and productivity A_i^s matches the sector-level expenditure share $\overline{\lambda}_{ij}^{s}$
- Intensity of labor disutility θ_i^s is such that $\ell_i^s = 1$ in the initial period;
- Nonpecuniary utility η_i^s matches the 2000 distribution of labor L_i^s:
- Migration costs χ_{it}^{sn} match the migration flow from 1999 to 2000 $\mu_{i,-1}^{sn}$.

Productivity A_i^s and trade costs τ_{ij}^{s}. We first construct the equation identifying trade costs τ_{ij}^{s} using the gravity equation and firm pricing equation, following Head and Ries (2001) and Eaton et al. (2016). The firm pricing equation is given by

$$P_{ij}^{s} = e_{ij}\tau_{ij}^{s}\frac{1}{A_i^s}(W_i^s)^{\phi_i^s}\prod_n (P_i^n)^{\phi_i^{ns}} = e_{ij}\tau_{ij}^{s}P_i^{s,dom}$$

and we normalize $\tau^s_{ii} = 1$ (so A^s_i fully captures the productivity). The gravity equation of trade shares is

$$\lambda^s_{ij} = \frac{(P^s_{ij})^{1-\sigma_s}}{(P^s_j)^{1-\sigma_s}}$$

so we have

$$\frac{P^s_{ij}}{P^s_{jj}} = (\frac{\lambda^s_{ij}}{\lambda^s_{jj}})^{\frac{1}{1-\sigma}} \tag{B.4}$$

Combining the two equations above, we get

$$\tau^s_{ij} = \frac{e_j P^{s,dom}_j}{e_i P^{s,dom}_i}(\frac{\lambda^s_{ij}}{\lambda^s_{jj}})^{\frac{1}{1-\sigma_s}} \tag{B.5}$$

We normalize the productivities $A^s_i = 1$ and set the wages so that $W^s_i L^{s,data}_i$ fits the data on value added in each sector (so we can match the net export flows). Then, we calibrate the "trade block" of $\{A^s_i, \tau^s_{ij}\}$ under the assumption that labor supply is fixed at $L^{s,data}_i$ and households find it optimal to supply $\ell^s_i = 1$, and calibrate the rest of the parameters so that our model endogenously generates $L^s_i = L^{s,data}_i$ and $\ell^s_i = 1$. This solves the following system of equations:

$$P_i = \prod (P^s_i)^{\alpha^s_i} \tag{pindex}$$

$$(P^s_j)^{1-\sigma} = \sum_i (P^s_{ij})^{1-\sigma_s} \tag{pindex}$$

$$\sum_s W^s_i L^{s,data}_i = P_i C_i + NX_i \tag{budget}$$

$$R^s_i = \sum_j \lambda^s_{ij}(\alpha^s_j P_j C_j + \sum_n \phi^{sn}_j R^n_j) \tag{goods market}$$

with the auxiliary variables

$$P^s_{ij} = \frac{1}{A^s_i}\tau^s_{ij}(W^s_i)^{\phi^s_i}\prod_n (P^n_i)^{\phi^{ns}_i} \tag{unit cost}$$

$$P^s_{i,dom} = \frac{1}{A^s_i}(W^s_i)^{\phi^s_i}\prod_n (P^n_i)^{\phi^{ns}_i} \tag{domestic}$$

$$\lambda^s_{ij} = \frac{(P^s_{ij})^{1-\sigma}}{(P^s_j)^{1-\sigma}} \tag{trade share}$$

$$\phi^s_i R^s_i = W^s_i L^s_i \tag{labor share}$$

The solution to this model gives the trade block parameters $\{A^s_i, \tau^s_{ij}\}$.

Disutility of labor. We calibrate θ^s_i such that $\ell^s_i = 1$ in equilibrium. In our calibration of

$\{A_i^s, \tau_{ij}^s\}$, we obtain C_i, W_i^s, P_i. Then the labor supply equation is

$$\theta_i^s (\ell_i^s)^{\varphi^{-1}} = v'(\ell_i^s) = \frac{W_i^s}{P_i} u'(\frac{C_i}{L_i})$$

so the calibrated value of θ_i^s that satisfy $\ell_i^s = 1$ is $\theta_i^s = \frac{W_i^s}{P_i} u'(\frac{C_i}{L_i})$.

Migration costs. We follow the literature and recover the migration frictions χ_i^{sn} from the observed migration flow μ_i^{sn} form the CPS. Assuming that bilateral migration frictions are symmetric in the initial period only ($\chi_{it}^{sn} = \chi_{it}^{ns}$) and normalizing own migration frictions to zero ($\chi_{it}^{ss} = 0$), the model's gravity equations for migration in Equation 23 imply

$$\log\left(\frac{\mu_i^{sn}\mu_i^{ns}}{\mu_i^{ss}\mu_i^{nn}}\right) = -\frac{2}{\nu}\chi_i^{sn} \tag{B.6}$$

so we can back out χ_i^{sn} for the US. For other countries, we assume the same migration costs.[3]

Nonpecuniary utility. Given the above calibrated parameters, we invert the realized labor supply $\{L_i^s\}$ to obtain the nonpecuniary utilities $\{\eta_i^s\}$ such that the model-implied L_i^s exactly match the data.

B.4.2 Calibration of the shocks

We calibrate the productivity, trade shocks, preference shocks, and the time-varying migration costs $\{A_{it}^s, \tau_{ijt}^s, \delta_{it}, \chi_{it}^{sn}\}_{t=2000}^{T_{data}}$. We use data from 2000-2012, so we calibrate 12 years of shocks, and assume these parameters are constant at the levels of $T = 2012$.

Since we have the initial values of productivity and trade costs, we match the *shocks* to these variables: $\hat{\tau}_{ijt}^s = \frac{\tau_{ijt}^s}{\tau_{ij0}^s}, \hat{A}_{it}^s = \frac{A_{it}^s}{A_{i0}^s}$. We calibrate $\{\hat{\tau}_{ijt}^s, \hat{A}_{it}^s, \delta_{it}, \chi_{it}^{sn}\}$ to match the following observed data:

- Changes in expenditure shares: $\hat{\lambda}_{ijt}^s = \frac{\lambda_{ijt}^s}{\lambda_{ij0}^s}$
- Changes in output prices in USD terms, observed from WIOD SEA.
- Net exports as a fraction of GDP: $NXGDP_{it} = \frac{NX_{it}}{VA_{it}}$
- Migration flows: μ_{it}^{sn}

[3] In practice, we can break symmetry and calibrate χ_i^{sn} by time-differencing migration flow across time – under this method, migration costs as the residual term of the Artuç et al. (2010) regression used to compute ν, used also in Caliendo et al. (2019); Dix-Carneiro et al. (2023). However, the calibrated migration costs have implausibly large noise, mainly because the migration flow values themselves are highly noisy and we're taking log differences of them; notably, the migration costs are highly heterogeneous across time, while time-differencing requires assumption of constant migration cost. Thus we consider this a more 'stable' approach, as we match the initial labor distribution exactly.

First, we can back out $\hat{\tau}^s_{ijt}$ directly from the gravity equation without solving for the full model. Indeed, From Equation B.5, we have

$$\hat{\tau}^s_{ijt} = \frac{\hat{e}_{jt}\hat{P}^{s,dom}_{jt}}{\hat{e}_{it}\hat{P}^{s,dom}_{it}}\left(\frac{\hat{\lambda}^s_{ijt}}{\hat{\lambda}^s_{jjt}}\right)^{\frac{1}{1-\sigma_S}} \tag{B.7}$$

But $\hat{e}_{jt}\hat{P}^{s,dom}_{jt}$ is precisely the changes in output prices in USD terms; hence the right-hand side is directly observable from data, and thus we obtain the left-hand side from the gravity equation.

Now we turn to productivity shocks $\hat{A}^s_{it}$, savings shocks δ_{it}, and the reallocation costs χ^{sn}_{it}. We use the full structure of the model by using the method of simulated moments: we solve the model given any sequence of shocks $\{\hat{A}^s_{it}, \delta_{it}\}$, and match the constructed output price data $\hat{P}^{s,dom}_{it} = \frac{P^{s,dom}_{it}}{P^{0,dom}_{it}}$, net exports as a share of GDP ($NXGDP_{it}$) and migration flows μ^{sn}_{it} respectively to exactly match the realized data.

C Foresight of the China Shock

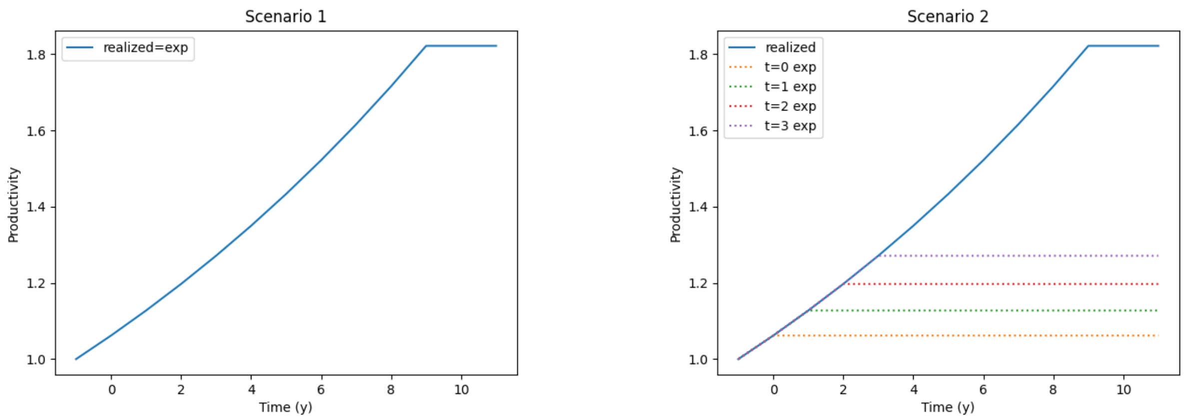
We discuss anticipation of the shock by the households of the model, as agents' foresight of the China shock is important in determining the economy's response to the shock. The literature on structurally estimating the effect of the China shock (Caliendo et al., 2019; Rodríguez-Clare et al., 2022; Dix-Carneiro et al., 2023) all implicitly assume that every agent in the economy at $t = T_0$ have perfect foresight of the full sequence of productivities for $t \in [T_0, T_{data}]$ including the China shock and makes forward looking choices, including sectoral reallocation and consumption-savings, anticipating the development of the full path of the China shock at the start of the model (usually 2000). If the China shock was truly a shock, this is equivalent to assuming that nobody knew of the productivity growth in 1999, but everyone woke up at 2000 and learned the full sequence of the China shock, including that it will plateau at around 2010 (Autor et al., 2021).[4] The problem with this approach is that the model implies a lot of front-loading in transition – wages will adjust incorporating not only the immediate shock but all future shocks, manufacturing workers in 2000 would have a higher desire to leave, and Chinese households will borrow large amounts if they foresaw the full extent of Chinese growth – and the calibrated parameters have to take extreme values to reconcile this with the observed migration and net exports.

We consider an alternative assumption – that agents face a *series* of unanticipated shocks for each t between T_0 and T_{data}. Specifically, in the baseline equilibrium with the realized China shock, at every year t between T_0 and T_{data}, agents learn the new fundamentals at time t $\Theta_t = \{\tilde{\tau}^s_{ijt}, \tilde{\delta}_{it}, \tilde{A}^s_i\}$, and agents (incorrectly) assume that the fundamentals are constant for $t' > t$. In this sense, every year between T_0 and T_{data} is a *China shock*.

To test the validity of this assumption, we estimate the response of our economy to a gradual productivity shock in the low-tech manufacturing sector of China over T_c years, but using two polar opposite assumptions about agents' foresight. In the first exercise, we assume that agents *do not foresee* the shocks in full: for T_c years, the agents face an unanticipated productivity shock every year, and makes decisions assuming that there are no more shocks onwards. In the second exercise, we assume instead, analogously to the literature, that agents in the model have perfect foresight of the full sequence of productivity shocks in $t = T_0 = 2000$. All remaining fundamentals are fixed at calibrated values in $t = T_0$, so the only deviation is the productivity shocks, and to highlight the role productivity shocks play in our model, we assume, for this thought exercise only, that the economy is in steady-state under the initial parameters at $T_0 = 2000$, so any transition dynamics can be fully attributed to the productivity shock.

Exercise 1. Gradual shock, no foresight. First we study the no-foresight assumption, as

[4] One of the reasons why the literature assumes this strong form of perfect foresight is computational tractability. Our modeling framework and solution algorithm (Section 3.2) allows us to bypass these challenges.



(a) Perfect foresight (b) Compare peg and float

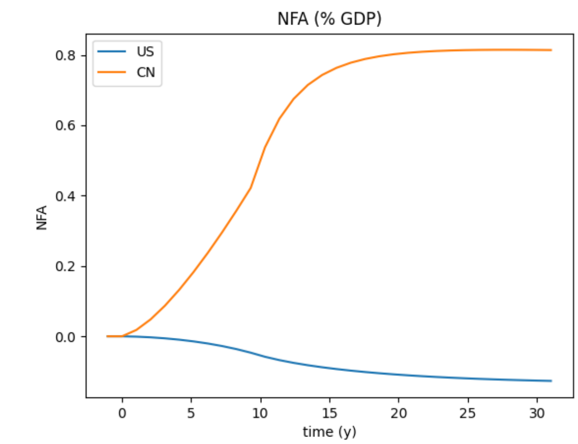
Figure C.1: Productivity growth in low-tech manufacturing. 6% per year for 10 years.

represented by the right panel of Figure C.1. In this case, the economy started at the 2000 levels, then Chinese productivity in low-tech manufacturing grows by 6% for 10 years, but every year, agents are surprised by the new productivity level; in this sense, every year is a China shock for 10 years.

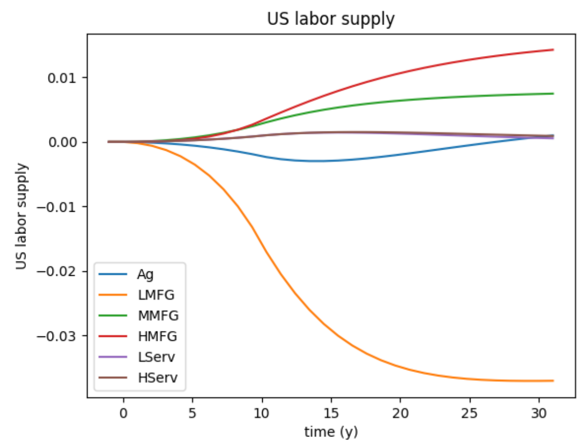
Figure C.2 plots the net foreign asset position, wage, labor reallocation, and unemployment response of the US in response to this shock. From the top left panel, we see that the net foreign asset B_{it} for the US is negative, while the net foreign asset for China is positive; so China saves while US borrows, in line with the observed data. In this sense, our channel – exchange rate peg interacting with a productivity shock – can *endogenously generate the savings glut*, as seen in Proposition 2 in Section 2.3. The top right plot, which shows labor reallocation, is analogous to the perfect foresight case, where workers slowly move out of the affected sector, and move into and out of other sectors depending on the input-output linkage.

The bottom two figures show the labor market's response in terms of wages and unemployment. Both plots match the empirical facts (Figure 1), theoretical prediction in Section 2.3, and matches evidence found in literature (Autor et al., 2013, 2021). Wages in the most affected sector fall, but wages in other sectors fall too because of the shock propagating to other sectors through input-output linkage. Lastly, the China shock induces unemployment in the US that grows over time as Chinese productivity grows over time, and reverts to zero as Chinese growth plateaus and the economy slowly adjusts to the new steady-state. Notably, while the directly exposed sector is most harmed, unemployment increases for workers in other sectors as well, because of input-output linkages.

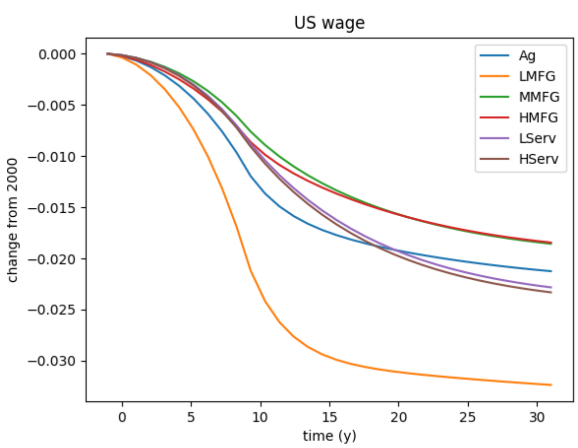
Exercise 2. Gradual shock, perfect foresight. Next we consider the perfect foresight model, as represented in the left panel of Figure C.1. In this case, the economy started at the 2000 levels,



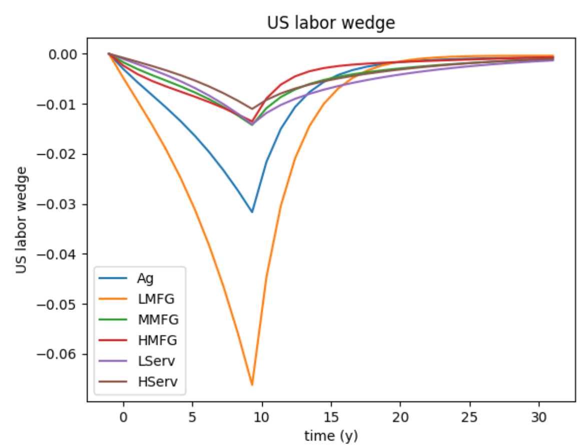
(a) NFA (% GDP)



(b) US labor reallocation



(c) US wage



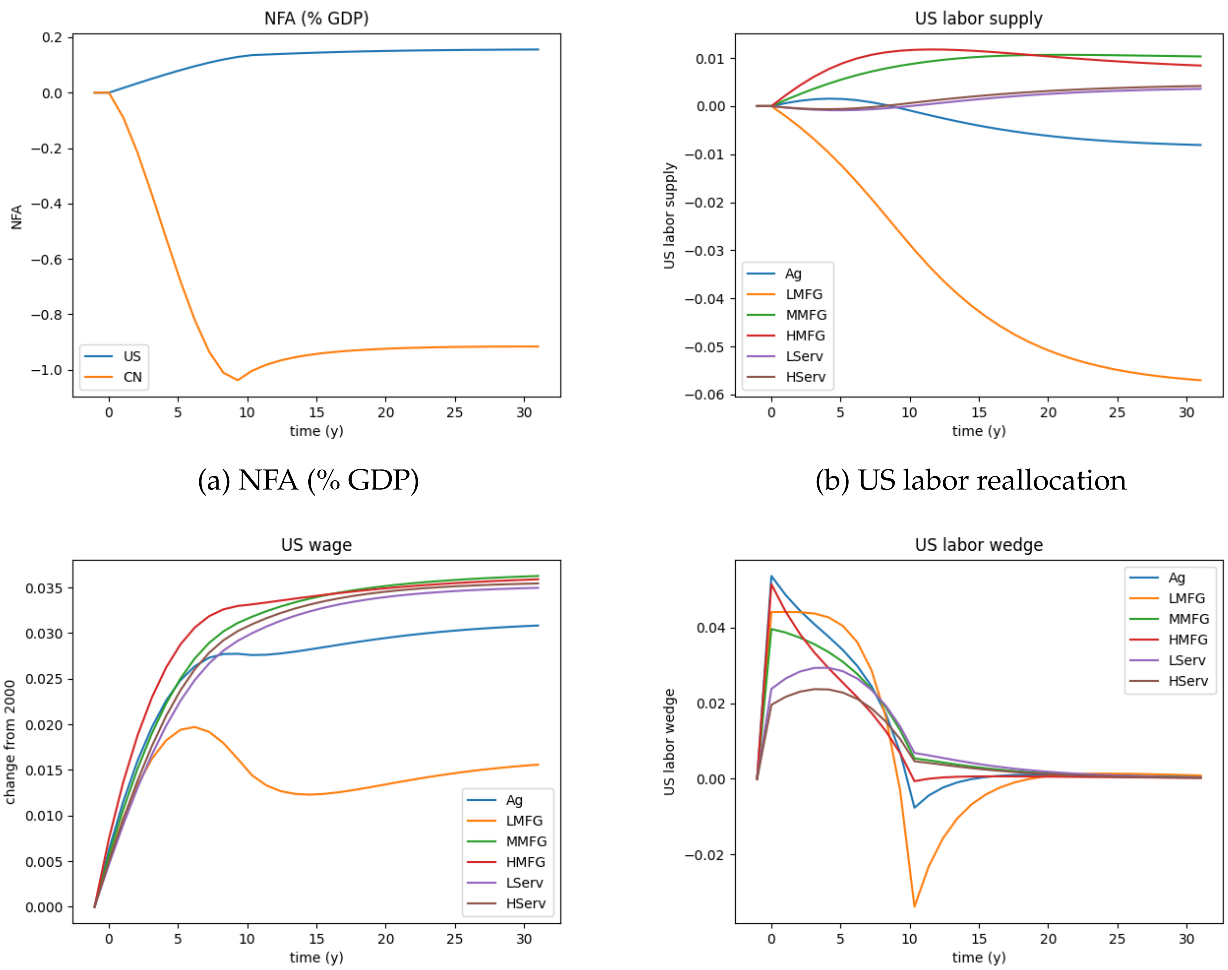
(d) US labor wedge

Figure C.2: Response of the US economy to the gradual shock with no foresight.

then Chinese productivity in low-tech manufacturing grows by 6% for 10 years, and all agents in the model expect the full path of Chinese productivity growth.

Figure C.3 plots the net foreign asset position, wage, labor reallocation, and unemployment response of the US in response to this shock. As the top left panel shows, if everyone in the model has perfect foresight of the China shock, Chinese agents have incentive to borrow because they foresee that their productivity in 10 years will be double their productivity today; likewise, US anticipates that Chinese goods will be much cheaper in the future, so it saves. The top right panel shows the labor reallocation response of the China shock, which is in line with what we would expect; since low-tech manufacturing in China grows, workers move out into other sectors. At the same time, some sectors grow more than others because of input-output linkages.

The bottom two panels of Figure C.3 show the wage and unemployment responses of the



(a) NFA (% GDP) (b) US labor reallocation

(c) US wage (d) US labor wedge

Figure C.3: Response of the US economy to the gradual shock with perfect foresight.

China shock. From the left panel, we see that wages *increase* in response to a Chinese productivity growth across all sectors. This is because of the combination of the fact that US borrows to consume more today, and home bias in the model. The most interesting response is the labor wedge, as observed in Figure C.3d. Since the economy faces a sudden surge in US goods demand (due to US saving and home bias), and both wages and labor supply are slow to adjust, there is *excess demand* for domestic goods – the US economy is overheated because of the expectation of future growth in China. As we see, neither the consumption-savings, nor the unemployment responses match those of the China shock.

We note that reality is somewhere in between these polar opposite assumptions (no foresight vs perfect foresight). Because the consumption-savings and labor market responses of the no foresight assumption are more consistent with the empirical evidence (such as Autor et al.

(2021)), in our main text, we calibrate and solve for the baseline and counterfactual economies under the assumption that households did not foresee the China shock.

D Solution Algorithm

This section presents the algorithms we use to estimate the model, calibrate the shocks, and perform counterfactual simulations. We assume convergence to the steady-state in T periods for a large enough T. In our baseline specification, we assume $T = 100$, so the economy converges to the new steady-state in 100 years. In our robustness tests, we compare the results with the results for $T = 200$ and verify that the results are quantitatively similar.

D.1 Variables and equations

As outlined in Section 3.2, we solve the economy in the *sequence-space*. Thus we consider a sequence of variables $\{X_t\}_{t=0}^{T}$, and each period's variables X_t comprise

$$X = (B_i, P_i, C_i, e_i, W_i^s, P_i^s, \ell_i^s, L_i^s, V_i^s).$$

Table D.1 lists the definitions of the variables of interest, and auxiliary variables we use in our solution algorithm.

Panel A. Variables of interest

Variable	Description
B_i	NFA in USD
P_i	Final goods price
C_i	Final goods consumption
e_i	Exchange rate
W_i^s	Sectoral wage
P_i^s	Sectoral goods price
ℓ_i^s	Per-worker labor supply
L_i^s	Distribution of labor
V_i^s	Worker value function

Panel B. Auxiliary variables

Variable	Description
R_i^s	Revenue of i in s
E_i^s	Expenditure of i in s
$\mu_i^{ss'}$	Worker transition matrix
P_{ij}^s	Unit price of good
λ_{ij}^s	Trade shares
i_{it}	Nominal interest rate

Table D.1: Variables to solve for

We denote the *auxiliary* variables as such because they can be directly computed from the variables in X:

$$R_i^s = \frac{W_i^s L_i^s}{\phi_i^s} \qquad \text{(Labor share)}$$

$$E_i^s = \alpha_i^s P_i C_i + \sum_n \phi_i^{sn} R_i^n \qquad \text{(Expenditure)}$$

$$\mu_i^{ss'} = \frac{\exp(\beta V_i^{s'} - \chi_i^{ss'})^{1/\nu}}{\sum_n \exp(\beta V_i^n - \chi_i^{sn})^{1/\nu}} \qquad \text{(Worker transition)}$$

$$P_{ij}^s = \frac{1}{e_{ij}} \tau_{ij}^s \frac{1}{A_i^s} (W_i^s)^{\phi_i^s} \prod_{s'} (P_i^{s'})^{\phi_i^{s's}} \qquad \text{(Unit cost)}$$

$$\lambda_{ij}^s = \frac{(P_{ij}^s)^{1-\sigma}}{\sum_l (P_{lj}^s)^{1-\sigma}} \qquad \text{(Trade share)}$$

$$\log(1 + i_{it}) = r_{it} + \phi_\pi \log(P_{it+1}/P_{it}) + \epsilon_{it}^{MP} \qquad \text{(Taylor rule)}$$

with China's interest rate i_{2t} identical to that of the US (peg and UIP).

We take the logs of the positive variables C, P, W, e, L, ℓ to ensure stability of our algorithm. Given the variables X_t, the equations of the quantitative model (in Section A.1) can be written as:

$$F_1(X_t) = p_i - \sum_s \alpha_i^s p_i^s \qquad \text{(price index)}$$

$$F_2(X_t) = \exp((1-\sigma)p_j^s - \sum_i \exp((1-\sigma)p_{ij}^s) \qquad \text{(sector price)}$$

$$F_3(X_t) = R_i^s - \sum_j e_{ji} \lambda_{ij}^s E_{js} \qquad \text{(goods market)}$$

$$F_4(X_t, X_{t+1}) = \exp(p_i + c_i) + \frac{1}{1+i} B_{i,t+1} - B_i - \sum_s \exp(w_i^s + \ell_i^s) \qquad \text{(HH budget)}$$

$$F_5(X_t, X_{t+1}) = (-\frac{1}{\gamma} c_i - p_i) - (-\frac{1}{\gamma} c_{i,t+1} - p_{i,t+1}) - \log(\beta(1+i_i)) - \log(\delta) \qquad \text{(Euler)}$$

$$F_6(X_t, X_{t+1}) = e_{t+1} - e_t + \log(1+i_i) - \log(1+i_1) \qquad \text{(UIP)}$$

$$F_7(X_t, X_{t+1}) = \exp(l_{i,t+1}^s) - \sum_n \mu_i^{ns} \exp(l_i^n) \qquad \text{(mig)}$$

$$F_8(X_t, X_{t+1}) = v_{is} - \frac{\exp(w_{is} + n_{is})}{\exp(l_{is} + p_{is})} u'(c_i) - \nu \log[\sum \exp(\frac{1}{\nu}(\beta v_{is}^{t+1} - \chi_{iss'}))] \qquad \text{(Value)}$$

$$\begin{aligned} F_9(\{w_{i,t-1}^s\}, X_t, X_{t+1}) = &(w_{is} - w_{is}^{t-1}) - \kappa_w [v'(\ell_{is}) - u'(c_{is}) \exp(w_{is} - p_i)] \\ &- \beta_w (w_s^{t+1} - w_s) \exp(l_s^{t+1} - l_s) \end{aligned} \qquad \text{(NKPC)}$$

This set of equations is the main set of equations we use to solve for the equilibrium. Note that the period t equilibrium conditions only depend on t, $t+1$ variables and the previous period wage.

D.2 Solving for the steady-state

We first solve for the long-run steady-state: an equilibrium with persistent net foreign asset positions (in USD) and relative wages. Per our assumptions, for China, which pegs to the US, we may have $B_i \neq 0$, and for countries other than China and the US, we have $B_i = 0$.[5] Given any values of the fundamentals and parameters in Table 1, and the terminal real NFA $\{B_i\}_i$, the steady-state comprises $2I + 5IS$ variables $X_T = (P_i, C_i), (W_i^s, P_i^s, L_i^s, \ell_i^s, V_i^s)$ that solve the following system of equations, written using the form in Section D.1:

$$G_{ss}(X_T) = \begin{pmatrix} F_1(X_T) \\ F_2(X_T) \\ F_3(X_T) \\ F_4(X_T, X_T) \\ F_7(X_T, X_T) \\ F_8(X_T, X_T) \\ F_9(X_T, X_T, X_T) \end{pmatrix} = \begin{pmatrix} 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \end{pmatrix} \tag{D.1}$$

taking advantage of the fact that in steady-state, $X_{T-1} = X_T = X_{T+1}$. The algorithm for solving for this steady-state is as follows: it robustly converges for any given parameters.

Step 1. Make an initial guess for the solution $X_T^{(1)}$.

Step 2. Update the initial guess of the solution $X_T^{(1)} \to X_T^{(2)}$ using the price index equation F_2, the value function and labor transition equations F_7, F_8: each of them are contraction mappings, so given the initial guess, we can iterate the function a finite number of times.

Step 3. Use **gradient descent** to update the guess $X_T^{(2)} \to X_T^{(3)}$ (we use 20 iterations with learning rate 10^{-12}).

Step 4. Use **Newton's method** on $G_{ss}(X_T)$ to update the guess $X_T^{(3)} \to X_T^{(4)}$, until the error tolerance $\|G_{ss}(X_T)\|$ is below a certain threshold (we use 10^{-20}).

The resulting set of variables $X_T^{(4)}$ is the set that solves the system G_{ss} given B_T. See Section D.5 for the bolded nonlinear solvers.

D.3 Estimation algorithm for pegged economy

Given any set of dynamic parameters and fundamentals in Table 1 and the initial conditions $\{w_{i,-1}^s, L_{i0}^s, B_i\}$, China's pegged exchange rate $e_2 = \bar{e}$, and any policy $\{T_{ijt}^s\}$, $\{\epsilon_{it}^{MP}\}$, the economy

[5] More generally, if we consider a model with more countries, for currency unions, we may have $B_i \neq 0$ for members of a union in steady-state, but $\sum_{i \in \mathcal{I}} B_i = 0$ for any currency union $\mathcal{I}$.

is defined in the sequence-space as the set of variables

$$X = \{X_t\}_{t=0}^{T} = \{(B_{it}, P_{it}, C_{it}, e_{it}, W_{it}^s, P_{it}^s, \ell_{it}^s, L_{it}^s, V_{it}^s)\}_{t=0}^{T}$$

that satisfy the equilibrium conditions. The period-t equilibrium conditions are given by

$$G_t(X_t, \{w_{it-1}^s\}, X_{t+1}) = \begin{pmatrix} F_1(X_t) \\ F_2(X_t) \\ F_3(X_t) \\ F_4(X_t, X_{t+1}) \\ F_5(X_t, X_{t+1}) \\ F_6(X_t, X_{t+1}) \\ F_7(X_t, X_{t+1}) \\ F_8(X_t, X_{t+1}) \\ F_9(\{w_{it-1}^s\}, X_t, X_{t+1}) \end{pmatrix} \tag{D.2}$$

The set of equations for the *path* $\{X_t\}_{t=0}^{T-1}$, given a terminal steady-state X_T, is

$$\mathcal{G}(\{X_t\}_{t=0}^{T-1}, X_T) = \begin{pmatrix} G_0(X_0, \{w_{i,-1}^s\}, X_1) \\ G_1(X_1, \{w_{i,0}^s\}, X_2) \\ \cdots \\ G_{T-2}(X_{T-2}, \{w_{i,T-3}^s\}, X_{T-1}) \\ G_{ss-1}(X_{T-1}, \{w_{i,T-2}^s\}, X_T) \end{pmatrix} = \begin{pmatrix} 0 \\ 0 \\ \cdots \\ 0 \\ 0 \end{pmatrix} \tag{D.3}$$

where G_{ss-1} is the period $T-1$ condition that links the sequence-space to the terminal steady-state, and is given by:

$$G_{ss-1}(X_{T-1}, \{w_{i,T-2}^s\}, X_T) = \begin{pmatrix} F_1(X_{T-1}) \\ F_2(X_{T-1}) \\ F_3(X_{T-1}) \\ \hat{F}_4(X_{T-1}) \\ C_{T-1} - C_T \\ F_7(X_{T-1}, X_T) \\ \hat{F}_9(\{w_{i,T-2}^s\}, X_{T-1}, X_T) \end{pmatrix} \tag{D.4}$$

The following are the differences between the last condition G_{ss-1} and a generic G_t:

- We replace the Euler equation with $C_{T-1} = C_T$, signifying that we have reached a terminal state.

- We replace the Household budget clearing $F_4(X_{T-1}, X_T)$ with

$$\hat{F}_4 = \begin{pmatrix} e_{iT-1} = \bar{e} & \text{if } i = 2 \\ \exp(p_i + c_i) - B_i - \sum_s \exp(w_i^s + \ell_i^s) & \text{if } i > 2 \end{pmatrix}$$

  We encode the fact that floating countries have bond zero, and that pegging China has its exchange rate 1. Note that we have not used the household budget constraint of US and China (by Walras, this is one condition). We get back to this.

- We remove the UIP condition F_6 and the labor migration equations F_8, which are forward-looking equations.

- In the NKPC F_9, we impose $w_s^T = w_s^{T-1}$, again signifying that we are in staedy-state by period T.

Technical note: all of this is necessary because our model is nonstationary and the exchange rate features a unit root.

Given our construction of $\mathcal{G}$, we implement our solution algorithm in two steps: inner loop and outer loop.

Inner loop. Solve for the *path* $X_{path} = \{X_t\}_{t=0}^{T-1}$ that solves $\mathcal{G}(X_{path}, X_T)$ given a terminal state X_T. In an abuse of notation, we remove the dependency of $\mathcal{G}$ X_T.

Step 1. Make an initial guess for $X_{path}^{(1)}$. Here it is important that the sequence $\{X_t\}$ *converges* to the terminal state X_T for the algorithm to be stable.

Step 2. Use **gradient descent** on $\mathcal{G}(X_{path})$ to improve the initial guess $X_{path}^{(1)} \to X_{path}^{(2)}$.

Step 3. Use **quasi-Newton's method** on $\mathcal{G}(X_{path})$ to update the guess $X_{path}^{(2)} \to X_{path}^{(3)}$. In practice we repeat until $\|\mathcal{G}(X_{path})\| < 10^{-8}$.

Step 4. Use **Levenberg-Marquardt algorithm** on $\mathcal{G}(X_{path})$ to fine-tune the guess $X_{path}^{(3)} \to X_{path}^{(4)}$. In practice we repeat until $\|\mathcal{G}(X_{path})\| < 10^{-10}$.

Step 3 requires quick construction and inversion of the Jacobian of $\mathcal{G}(X_{path})$, which is a large matrix (in our main specification, with $I = S = 6$ and $T = 100$, the Jacobian has dimension 20000×20000). We have knowledge of the structure of $\mathcal{G}$: each time t equation G_t depends only on X_t, X_{t+1} and $\{w_{i,t-1}^s\}$. Thus we know the sparsity structure of the Jacobian (i.e. where all the nonzero elements are). so we use automatic differentiation (autodiff) to speed up this process, and construct the Jacobian $J_{\mathcal{G}}$ as a sparse matrix. Then we use Intel's PARDISO package[6] to quickly invert $J_{\mathcal{G}}$.

[6]See https://www.intel.com/content/www/us/en/resources-documentation/developer.html

Outer loop. Solve for the X_T that is consistent with the path X_{path}.

Step 1. Start from an initial guess of $B_T^{(1)}$. We only need to keep track of China's (or pegged countries') bond position, as the floaters will have $B_T = 0$.

Step 2. Given $B_T^{(i)}$, solve for $X_T^{(i)}$ using the steady-state solution (Section D.2).

Step 3. Given $X_T^{(i)}$, solve for $X_{path}^{(i)}$ (inner loop).

Step 4. Using $X_{T-1}^{(i)}$ and China's Household budget constraint, find $B_{T,implied}^{(i)}$.

Step 5. The map $B_T^{(i)} \to B_{T,implied}^{(i)}$ is a monotonically decreasing map. Find the unique fixed point B_T by iterative search, using **secant-bisection**.

Once the outer loop converges, we have a solution in the sequence-space $\{X_t\}$. When $I = S = 6$ and $T = 100$, with our current code, the solution is usually found between 1-3 minutes on a Dell PowerEdge R940xa server (208 cores, 3TB RAM) with a NVIDIA Tesla V100 (32GB) GPU accelerator.

D.4 Estimation algorithm for floating economy

For the floating economy, we first replace the auxiliary condition on China's monetary policy with an independent Taylor rule:

$$\log(1 + i_{2t}) = r_{2t} + \phi_\pi \log(P_{it+1}/P_{it}) + \epsilon_{2t}^{MP}$$

And we replace the 'linking' condition to the terminal steady-state as

$$G_{ss-1}^{float}(X_{T-1}, \{w_{i,T-2}^s\}, X_T) = \begin{pmatrix} F_1(X_{T-1}) \\ F_2(X_{T-1}) \\ F_3(X_{T-1}) \\ F_4(X_{T-1}) \\ C_{T-1} - C_T \\ F_7(X_{T-1}, X_T) \\ \hat{F}_9(\{w_{i,T-2}^s\}, X_{T-1}, X_T) \end{pmatrix} \tag{D.5}$$

where the difference between this and the pegged case is that we impose $B_T = 0$ for all countries. With this in mind, the solution algorithm is as follows:

Step 1. Solve for the long-run steady-state X_T consistent with $B_T = 0$.

Step 2. Make an initial guess for $X_{path}^{(1)}$. Here it is important that the sequence $\{X_t\}$ *converges* to the terminal state X_T for the algorithm to be stable.

Step 3. Use **gradient descent** on $\mathcal{G}^{float}(X_{path})$ to improve the initial guess $X^{(1)}_{path} \to X^{(2)}_{path}$.

Step 4. Use **quasi-Newton's method** on $\mathcal{G}^{float}(X_{path})$ to update the guess $X^{(2)}_{path} \to X^{(3)}_{path}$. In practice we repeat until $\|\mathcal{G}^{float}(X_{path})\| < 10^{-8}$.

Step 5. Use **Levenberg-Marquardt method** on $\mathcal{G}(X_{path})$ to fine-tune the guess $X^{(3)}_{path} \to X^{(4)}_{path}$. In practice we repeat until $\|\mathcal{G}^{float}(X_{path})\| < 10^{-10}$.

The solution in Step 5 corresponds to the solution of the floating economy, and there is no need for an outer loop. This is because under a floating economy, the model is stationary, and we *know* which steady-state we converge to.

D.5 Nonlinear solver algorithms

This subsection describes the generic nonlinear solvers we use in our solution algorithms.

Gradient descent. Given a function $f : \mathbb{R}^n \to \mathbb{R}^n$, we approximate the root of f by applying gradient descent on $g = \|f\|_2^2 = \sum_i f_i^2$.

Input: function $g = \|f\|_2^2$; gradient ∇g of g; learning rate λ; number of iterations m; tolerance tol.

Algorithm:

Step 1. Start from an initial guess $x^{(0)}$.

Step 2. Evaluate ∇g, the gradient of g, at $x^{(i)}$.

Step 3. Update the guess $x^{(i+1)} = x^{(i)} - \lambda \cdot \nabla g(x^{(i)})$ for sufficiently small λ.

Step 4. Repeat 2-3 for m iterations, terminate if $g(x^{(i+1)}) < tol$.

Note. In practice, this is too slow to converge to the root. We use this to *update* the initial guess, to feed in to the next solvers.

Newton's method. Given a function $f : \mathbb{R}^n \to \mathbb{R}^n$, we approximate the root of f by Newton's method on f.

Input: f, the function; J, the Jacobian J_f of f; $g = \|f\|_2^2$; number of iterations m; tolerance tol.

Algorithm:

Step 1. Start from an initial guess $x^{(0)}$.

Step 2. Use autodiff to compute J_f at $x^{(i)}$

Step 3. Use PARDISO to evaluate $J_f(x^{(i)})^{-1} f(x^{(i)})$.

Step 4. Update $x^{(i+1)} = x^{(i)} - J_f(x^{(i)})^{-1} f(x^{(i)})$; u

Step 5. Repeat 2-4 for m iterations, terminate if $g(x^{(i+1)}) < tol$

Note. Newton's algorithm requires a good initial guess. In static problems (solving for the terminal state), we use parts of the equation (which are contraction mappings) to construct the initial guess close to the solution, In dynamic problems, our initial guess is close to the terminal steady-state: this 'anchors' the problem and allows for convergence. But for efficiency reasons, we use the quasi-Newton method below for the high-dimensional dynamic problem.

Quasi-Newton's method. Given a function $f : \mathbb{R}^n \to \mathbb{R}^n$, we approximate the root of f by quasi-Newton's method on f.

Input: f, the function; J, the Jacobian J_f of f; $g = \|f\|_2^2$; grid s; number of iterations m; tolerance tol.

Algorithm:

Step 1. Start from an initial guess $x^{(0)}$.

Step 2. Use autodiff to compute J_f at $x^{(i)}$. Here it is essential that our autodiff procedure is sparse-aware, that is, aware of the nonzero elements of J_f.

Step 3. Use PARDISO to evaluate $dx = J_f(x^{(i)})^{-1} f(x^{(i)})$.

Step 4. Construct *candidate* updates $x(s) = x^{(i)} - s \cdot dx$ for a grid s. In practice we use a linear grid from 0.1 to 5.

Step 5. Compute $g(x(s))$ for each s and update $x^{(i+1)}$ to be $x(s)$ with the minimal $g(x)$.

Step 6. Repeat 2-4 for m iterations, terminate if $g(x^{(i+1)}) < tol$.

Note. The advantage of this approach is as follows: the bottleneck in Newton's method is computing and inverting the Jacobian $J_f(x^{(i)})$. By searching over a full grid after each computation of $J_f(x)^{-1} f(x)$, we can effectively search for more candidates with minimal time cost. In reality, Newton's method can overshoot in the first few steps so it's better to have small s, whereas closer to the root, the optimal s seems to be $2 - 4$. This may be due to the fact that the Jacobian is singular near the solution – smallest norm eigenvalue reaches zero – and it is known that a coefficient s with the multiplicity of the root gets us to quadratic convergence.

Levenberg-Marquardt Method. Given a function $f : \mathbb{R}^n \to \mathbb{R}^n$, we approximate the root of f by Levenberg-Marquardt algorithm.

Input: f, the function; J, the Jacobian J_f of f; $g = \|f\|_2^2$; dampening parameter λ; number of iterations m; tolerance tol.

Algorithm:

Step 1. Start from an initial guess $x^{(0)}$, and

Step 2. Use autodiff to compute J_f at $x^{(i)}$. Here it is essential that our autodiff procedure is sparse-aware, that is, aware of the nonzero elements of J_f.

Step 3. Compute $A = J^T J + \lambda \cdot (diag(J^T J))$ where $J^T J$ is the transpose of J multiplied by J, and $diag(M)$ is the matrix of diagonal entries of M.

Step 4. Use PARDISO to construct candidate update $x_n = x^{(i)} - A^{-1} J^T f(x^{(i)})$.

5-1. If $g(x_n) > g(x^{(i)})$, multiply λ by λ_{up}, and return to Step 3.

5-2. If $g(x_n) < g(x^{(i)})$, accept $x^{(i+1)} = x_n$, and divide λ by λ_{down}.

Step 6. Terminate if $g(x^{(i+1)}) < tol$, or $i = M$. Otherwise return to Step 2.

Heuristically, this allows us to get *closer* to the solution faster than quasi-Newton. In practice we use $\lambda_{up} = 2$ and $\lambda_{down} = 5$ (this is called *delayed gratification*.)

Secant-Bisection. Given a decreasing function $f : \mathbb{R} \to \mathbb{R}$, find x^* such that $f(x^*) = x^*$. Useful when the evaluation of f involves solving a high-dimensional nonlinear system in the background (see above).

Algorithm:

Step 1. Start from an initial guess $x^{(0)}$.

Step 2. Evaluate f at $x^{(0)}$. If $f(x^{(0)}) > x^{(0)}$, then we know $x^* > x^{(0)}$. Set $x^{(1)} = x^{(0)} + s(f(x^{(0)}))$ for small s, and iterate until we find $x^{(i)}$ such that $f(x^{(i)}) < x^{(i)}$, therefore $x^{(i)} > x^*$.

Step 3. Given $x_{lb} \leq x^{(i)} \leq x_{ub}$ with knowledge that $x^* \in [x_{lb}, x_{ub}]$, evaluate f at $x^{(i)}$. If $f(x^{(i)}) > x^{(i)}$, then replace x_{lb} with $x(i)$; otherwise replace x_{ub} with $x^{(i)}$.

Step 4. Bisection method would update $x_b^{(i+1)} = \frac{x_{ub}+x_{lb}}{2}$. Secant method would update $x_s^{(i+1)}$ as the intersection of the line connecting $(x_{ub}, f(x_{ub}))$ and $(x_{lb}, f(x_{lb}))$ and the x-axis. We update $x^{(i+1)} = sx_s^{(i+1)} + (1-s)x_s^{(i+1)}$ for some step size $s \in (0, 1)$. (In practice we use $s = 0.9$ by heuristics.)

Step 5. Repeat until convergence.

This method is useful because bisection is too slow (if evaluation takes 1 minute, and we want error margin 10^{-5}, we need 16 evaluations; whereas secant method is much faster for 'regular' functions, it may get stuck in corner. The hybrid method converges quickly – within 3-5 attempts maximum – to the fixed point within desired tolerance.

E Robustness: Quantitatives

E.1 Alternative monetary policy

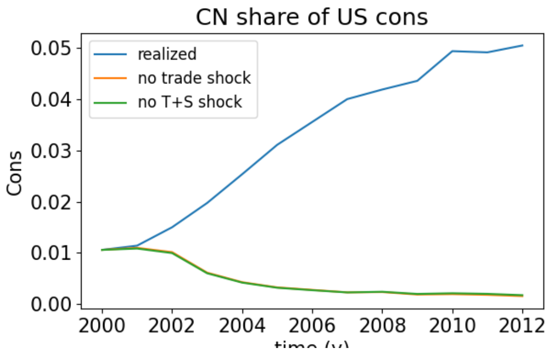
In our main text, we assumed that the floating countries (US and the world except China) used a Taylor rule targeting CPI inflation. This is not an 'optimal' monetary policy rule, as we do not have divine coincidence: targeting price inflation does not adequately target the nominal friction – labor wedge – in the economy. As we highlighted in the discussion in Section A of this supplement, in this case, the recession may spill over to the nontraded sectors, resulting in potentially high aggregate unemployment, not just manufacturing.

In this subsection, we redo the exercises in Section 4.2 (Reevaluating the China shock), except we replace the monetary policy rules, both for the realized economy and the counterfactual economy without the China shock or the peg, with a Taylor rule that targets the employment-weighted labor wedge:

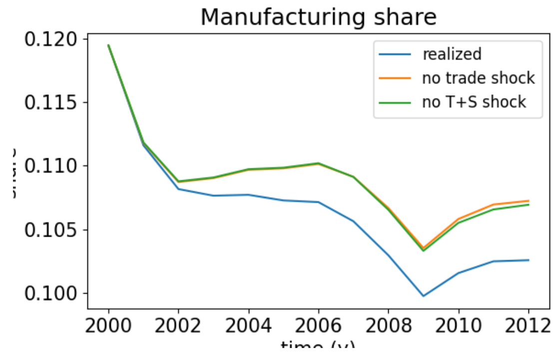
$$\log(1 + i_{it}) = r_{it} + \phi_{og}\left(\sum_s \frac{L^s_{it}}{\bar{L}_i}\left(v'(\ell^s_{it}) - \frac{W^s_{it}}{P_{it}u'(C_{it})}\right)\right). \tag{E.1}$$

We note that a change in monetary policy changes the price indices and the relative savings of each country. As such, we need to recalibrate our shocks to the economy $\{A^s_{it}, \delta^s_{it}\}$ to ensure that the resulting equilibrium under our realized shocks correspond to the realized economy in the targeted moments. Thus we recalibrate the China shock for the purpose of this exercise. We also note that the choice of employment-weighted labor wedge is a 'rule of thumb' choice. We study the optimal weights, and optimal monetary policy, under such environments, in a companion work in progress.

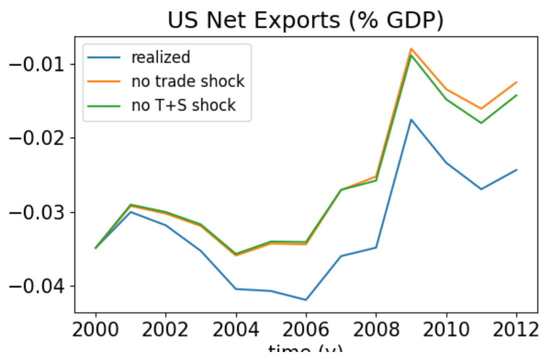
The results under the alternative monetary policy are shown in Figure E.1 and Table E.1. The decline in manufacturing as a result of the China shock is still larger than estimated in the literature, with the estimate being 700 thousand jobs. The deficit explained by the China shock is smaller (0.82% of GDP each year, compared to 2.25% in the baseline model) but still significant. The aggregate unemployment is close to zero, suggesting that the aggregate level of unemployment is primarily caused by the CPI-inflation targeting Taylor rule. The US economy balances between unemployment in manufacturing and overheating in services.



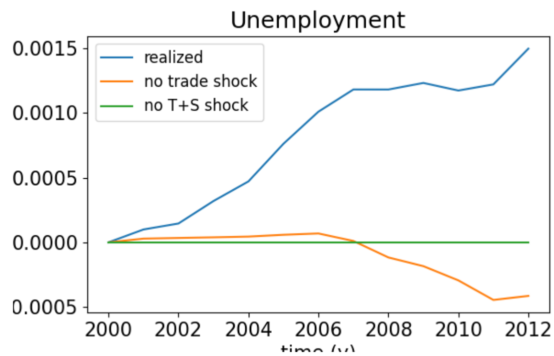
(a) CN import penetration



(b) Manufacturing share



(c) Net exports (% GDP)



(d) Unemployment rate

Figure E.1: Response of the economy to the China shock, alternative monetary policy.

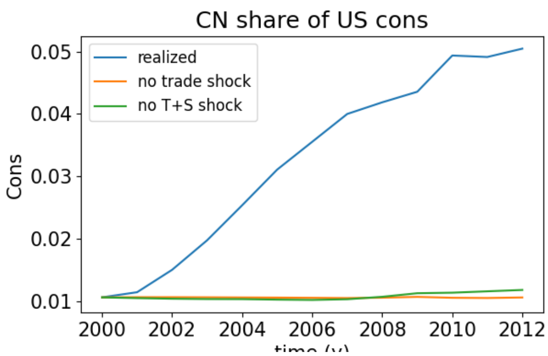
Effect of China shock					
	Alt MP	main text	CDP19	RUV22	DPRT23
MFG jobs lost	700k	991k	550k	498k	530k
Deficit (% GDP)	0.82	2.25	N/A	N/A	0.8
Unemployment (%)	0.095	3.04	N/A	1.4	0
Welfare gains	0.215%	0.183%	0.2%	0.229%	0.183%
Wage rigidity	O	O	X	O	X
Search friction	X	X	X	X	O
Cons-savings	O	O	X	X	O
ER peg	O	O	X	X	X

Table E.1: Effects of the China shock, alternative definition

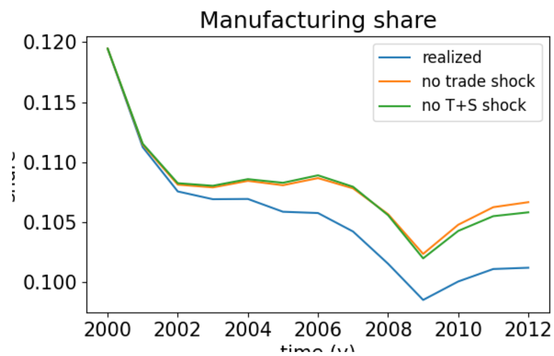
E.2 Alternative China Shocks

In our main text, our baseline assumption on the counterfactual 'no China shock' economy was an economy where productivity A_{it}^{s} and trade costs τ_{ijt}^{s} for China are fixed at the 2000 level. In this subsection, we redo the exercises in Section 4.2 (Reevaluating the China shock) with an alternative definition by defining the 'no China shock' economy as an economy where productivity A_{it}^{s} and export trade costs τ_{ijt}^{s} are calibrated to values such that λ_{ijt}^{s} for China is fixed at the 2000 values. This would be closer to specifications that calibrate the China shock to match regression coefficients on observed growth in export shares, used in Caliendo et al. (2019); Rodríguez-Clare et al. (2022).

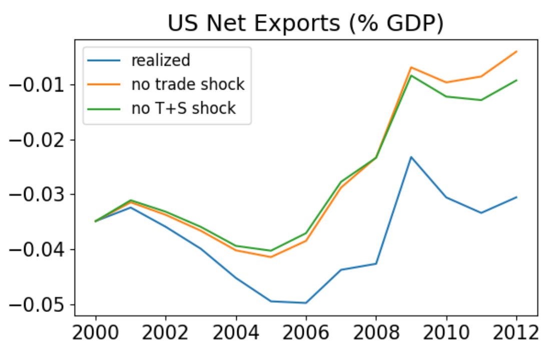
The results under this alternative China shock are similar to our results in the main text. As we see from the first subfigure of Figure E.2, the counterfactual economy without the China shock has Chinese share of US consumption flat. Even in this case, the manufacturing jobs lost, trade deficit, and unemployment numbers are smaller than our baseline results but still significantly larger than the literature's estimates, highlighting the relevance of the exchange rate peg. Moreover, since China's growth is smaller, under this specification, we get a *smaller* welfare gain from the China shock.



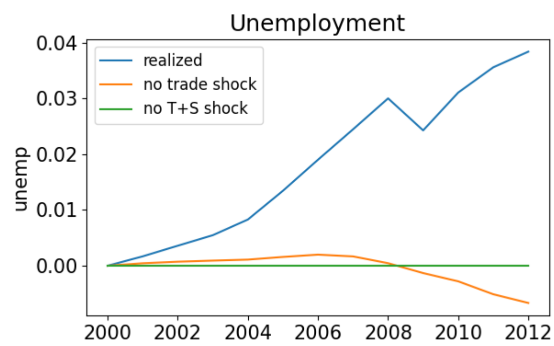
(a) CN import penetration



(b) Manufacturing share



(c) Net exports (% GDP)



(d) Unemployment rate

Figure E.2: Response of the economy to the China shock, alternative measure.

Effect of China shock					
	Alt shock	baseline	CDP19	RUV22	DPRT23
MFG jobs lost	822k	991k	550k	498k	530k
Deficit (% GDP)	1.50	2.25	N/A	N/A	0.8
Unemployment (%)	2.02	3.04	N/A	1.4	0
Welfare gains	0.145%	0.183%	0.2%	0.229%	0.183%*
Wage rigidity	O	O	X	O	X
Search friction	X	X	X	X	O
Cons-savings	O	O	X	X	O
ER peg	O	O	X	X	X

Table E.2: Effects of the China shock, alternative definition

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