When is it Too Late to Roll Back a Sectoral Transition? *

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Abstract

Sectoral transitions displace workers and often generate opposition. Politicians promise to restore a golden age by rolling back these transitions, e.g., reversing globalization, or bringing back coal. We study how workers' support for rolling back a sectoral transition evolves over time, using a life-cycle model with sector-specific skill accumulation on the job. We find that workers who initially oppose a transition might end up supporting it, as they "move on" and progressively lose their comparative advantage in their old activity. In the aggregate, workers' support for the transition typically follows a wave pattern: the economy experiences a honeymoon phase with increasing support, followed by a backlash phase, and finally an acceptance phase where workers move on and rolling back the transition is not longer feasible politically. After documenting clear evidence of this wave pattern in three decades of American polling on international trade, we use a quantitative version of our model to explore how more generous social insurance would have affected the timing of this wave in US attitudes towards trade, and the implications of a China shock 2.0.

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1 Introduction

Sectoral transitions shift economic activity across industries and displace workers along the way. The U.S. economy has experienced several such transitions over the past decades: the contraction of manufacturing due to import competition, the automation of routine work and, now, the diffusion of generative artificial intelligence. These transitions inflict substantial earnings losses on displaced workers and reliably generate opposition (Autor et al., 2020; Fajgelbaum et al., 2020; Gallego and Kurer, 2022). Politicians often appeal to these workers by promising to roll back these transitions and restore a golden age by, e.g., reversing trade liberalization, bringing back coal, reviving the steel industry, or shutting down AI data centers. Over the past decade, this type of restorationist platform has moved from the fringes of politics to its center in the United States and much of Europe (Rodrik, 2021; Caprettini and Voth, 2020).

Yet, the economy adapts as the transition unfolds. Displaced workers reallocate to other industries; the skills they leave behind depreciate over time; they accumulate different ones; and new cohorts enter the labor market having never specialized in the old activity in the first place. In other words, the workforce courted by restorationist policies dissolves over time. Many of these workers "move on" over time: their comparative advantage changes progressively and they may no longer want their old jobs back. The distribution of skills is indeed very different today than it was twenty years ago.

These observations raise a question at the heart of restorationist politics: who is left to oppose a sectoral transition as time passes? And when does it become *too late* politically to roll back a sectoral transition? Despite the prominence of these questions in contemporary policy debates, we know surprisingly little about how political support for a sectoral transition evolves over time.

In this paper, we develop a life-cycle general equilibrium model of a labor-displacing transition (e.g. offshoring, automation, or generative AI) in which workers' political support for a transition evolves endogenously as they are displaced, reallocate across sectors, let their old skill depreciate, and accumulate different ones. There is a continuum of sectors or occupations which are complements in the production of a final numeraire consumption good. Each sector produces using either domestic labor or a labor-saving factor (e.g. imported goods, robots, or AI). The labor-saving factor becomes cheaper over time, displacing workers pro-

gressively from one sector after another. Workers are finitely lived, specialize in a sector at the start of their career, accumulate further skills on the job, and lose those skills gradually when supplying labor elsewhere. At every instant, workers may vote either to maintain the status quo transition or roll it back by, say, imposing prohibitive tariffs to reverse globalization. Crucially, rolling back the transition reverts the technology to its original state but *not* workers' skills: policy can affect market prices, not workers' past experiences. Individual values aggregate into political outcomes based on a flexible voting hazard in the tradition of probabilistic voting (Lindbeck and Weibull, 1987; Persson and Tabellini, 2000).

Three conceptual insights emerge from our analysis. First, a worker's support for a given transition can flip over time: some workers support the transition at first, only to oppose it later on; on the contrary, some workers oppose it initially, only to support it at a later point. To understand why, consider first a worker who has not been displaced *yet* by the transition. Their real wage increases over time, since the labor-displacing factor is adopted more widely in occupations that complement theirs. While this worker might support the transition at first, they will eventually be displaced as the labor-saving factor becomes cheaper. At this point, the worker prefers rolling back the transition that they once supported.

Now, consider instead a worker who has *already* been displaced by the transition. Once they abandon their declining sector, their skills in that sector depreciate gradually. At the same time, the worker starts accumulating different skills in the sector they moved to. As the worker's comparative advantage evolves over time, they eventually "move on" and end up supporting a transition that they opposed in the first place. As a result, the constituency for the restorationist agenda erodes endogenously, even among those that this agenda was meant to help. The entry of new cohorts accelerates this trend, as they never acquire the skills that would be needed if the transition were rolled back. Importantly, undoing a transition by reverting factor prices is not the same as never having experienced the transition in the first place: the skill distribution has changed in the interim, so outcomes that were favored in the past might no longer be politically feasible. Many workers may be worse off as a result of the transition; and yet, there might be little appetite to revive long-gone industries which are mismatched to workers' current skills.

Our second (and related) conceptual insight is that *aggregate* support for a labor-displacing transition typically follows a *wave* pattern. During the initial honey-

moon phase, most workers enjoy cheaper consumption goods and support the transition, while displacement is confined to a few occupations. Then comes a backlash phase as more and more workers are displaced, earn less, and now oppose the transition. Finally, the economy enters an acceptance phase during which support for the transition recovers, as more workers move on and new cohorts enter the labor market. An immediate implication of this wave pattern is that there exists a point past which the pressure to roll back the transition abates and, potentially, reversing it is no longer feasible politically.

Our third conceptual insight is that worker's voting behavior, as captured by the shape of their *voting hazard*, is key for the timing and depth of the wave pattern in aggregate support. This voting hazard maps workers' continuation values to their probability of supporting the status quo transition or rolling it back. In principle, this hazard could either be binary, in which case each worker votes for the option that delivers the higher value (Mayer, 1984; Fernández and Rodrik, 1991; Hassler et al., 2003), or it could be much flatter and smoother, reflecting idiosyncratic preferences, identity, partisanship, or rational inattention (Lindbeck and Weibull, 1987; Grossman and Helpman, 1996a; Dixit and Londregan, 1998; Matějka and Tabellini, 2021). Perhaps paradoxically, we show that a *flatter* voting hazard at the micro level can translate into *larger waves* in support at the macro level. To understand why, consider a scenario where a slim majority of workers gains from a transition while the rest suffer increasingly at first and eventually move on. With a discontinuous hazard, the slim majority always prevails: the losses of an intensely affected minority never register and there is no wave pattern in the aggregate. In contrast, the intensity of losses matters when the hazard is smoother and flatter: a "vocal" minority of workers who lose from the transition plays a disproportionately larger role, resulting in a wave in aggregate support.

Having made these points conceptually, we then document clear empirical support for the wave pattern predicted by the model, using three decades of American polling on attitudes towards international trade. We use surveys that ask the *same* opinion question over an extended period, since attitudes are notoriously difficult to compare across questions. In particular, we exploit a Gallup poll which has asked Americans since 1995 whether they view foreign trade more as an opportunity rather than a threat. The results reveal a distinctive wave pattern: support rose through the 1990s as US workers enjoyed real wage gains from cheaper im-

ported goods; it declined steadily after 2000 as the "China shock'" unfolded and displaced workers; and it has recovered markedly since. Polling data from Pew since 2002 confirms the timing of the backlash and the subsequent recovery.

The final part of the paper takes the model to the data in a quantitative application to international trade. We extend the conceptual model along dimensions that are important to match the data: infrequent reallocation opportunities, noisy switching decisions generate large gross worker flows across sectors, an option to exit the labor force, and a progressive tax-and-transfer system as in Bénabou (2002) and Heathcote et al. (2017). We discipline the transition path with the relative price of imports from newly industrialized Asia, rank sectors by their import penetration in the 21^{st} century, and estimate the accumulation and specificity of skills from panel data on wages and on displaced workers.

The shape of workers' voting hazard is important for our quantitative analysis, and we make empirical progress in measuring it. We start by combining commuting-zone estimates of the earnings losses from Chinese import competition with voting records from the 2016 presidential election. We then non-parametrically regress the log-odd (or logistic function) of the Trump vote share as a function of workers' earnings losses at the commuting zone-level — controlling for past Republican vote. The relationship that we obtain is almost perfectly linear, which is consistent with logistic voting hazard (McFadden, 1974; Persson and Tabellini, 2000). In particular, the data clearly rejects the binary hazard. Overall, we find that voting responds strongly on the intensive margin: opposition to trade comes disproportionately from a minority with much at stake rather than from a wholesale shift of the majority.

We will use our calibrated model to conduct two exercises. The first one is restrospective: we will investigate how more progressive tax and transfer programs could have dampened the backlash against import competition in the US and changed the timing of the wave in support for trade integration. Our second exercise is prospective: we will use our structural model to forecast the political consequences of a potential "China Shock 2.0," which is now concentrated in higher-skill industries (Autor and Hanson, 2025).

Our paper contributes to a literature on sectoral transitions and their labor market consequences. Existing work documents large and persistent earnings losses for workers displaced by import competition (Autor et al., 2013, 2016; Dix-

Carneiro and Kovak, 2017), automation (Acemoglu and Restrepo, 2020, 2022), or, more generally, technological change that makes workers' skills obsolete (Braxton and Taska, 2023). Accounting for workers' skill specificity is important to explain how new technologies affect income inequality (Violante, 2002; Kambourov and Manovskii, 2009a) and how quickly the economy can adopt them (Adão et al., 2024). In our model, workers accumulate general and specific skills on-the-job and dis-accumulate those off-the-job (Lise and Postel-Vinay, 2020). Workers are displaced from one occupation after another as falling automation or import prices erode labor's comparative advantage across tasks (Acemoglu and Restrepo, 2018, 2019, 2022). Compared to this existing literature, our paper studies the political economy of labor-displacing transitions and how the political support evolves as these transitions progress.

We also speak to a literature focusing on the speed of technological transitions. Slowing down automation or import competition can be optimal to improve equity (Guerreiro et al., 2022; Thuemmel, 2023; Costinot and Werning, 2023; Lehr and Restrepo, 2023) and even efficiency when displaced workers are unable to perfectly smooth consumption (Beraja and Zorzi, 2024). In prior work (Grigsby and Zorzi, 2026), we showed that the distribution of earnings losses varies non-linearly or even non-monotonicially with the pace of a technological transition. Relative to this literature, we investigate how the political support for a given transition changes *over time* as this transition unfolds. Importantly, letting a labor-displacing transition play out for longer is conceptually different from speeding it up: skill accumulation takes time and workers' comparative advantage changes gradually.

Our work connects to the literature on the political economy of declining industries. Empirical work has documented the political fallout of trade shocks: import competition has revived a protectionist sentiment (Margalit, 2011; Di Tella and Rodrik, 2020; Fajgelbaum et al., 2020; Goldberg and Reed, 2023) and polarized the electorate (Autor et al., 2020; Colantone and Stanig, 2018). Similarly, automation has had a profound impact on political attitudes (Gallego and Kurer, 2022; Frey et al., 2018). Going forward, artificial intelligence has the potential to disrupt labor markets and have lasting political consequences (Anelli et al., 2021; Magistro et al., 2026). The insights that we develop in this paper apply to all these contexts.

On the theory front, a large body of work studies the government's incentives to protect declining industries in order to shelter its workers (Mussa, 1974;

Hillman, 1982) or cater to special interests (Grossman and Helpman, 1994, 1996b; Brainard and Verdier, 1997). In particular, Krusell and Ríos-Rull (1996) study an economy where skilled incumbents with vested interests can block technology adoption. While this literature works with static models or focuses on long-term growth, we study slow-moving transitions that displace workers and show that political support for these transitions is characterized by a wave pattern over time: support builds at first, it recedes, and eventually picks up again as more workers move on and new cohorts enter the labor market. We also document that this predicted wave pattern is consistent with evidence on US attitudes towards trade. The dynamic nature of our analysis connects to papers studying fluctuations in protectionism over the business cycles (Bagwell and Staiger, 1995; Barattieri et al., 2021). The mechanism that we propose is very different, however, and relies on skill specificity which is absent from these papers.

A related literature models households' voting explicitly (Fernández and Rodrik, 1991; Alesina and Passarelli, 2019) and studies how today's policy decisions affect the government' ability to carry out reforms in the future (Dewatripont and Roland, 1992; Coate and Morris, 1999; Hassler et al., 2003). Today's transition also shapes tomorrow's political constituency in our model: workers are displaced from their occupation, affecting which skills they accumulate. As a result, the pool of individuals who support rolling back a transition erodes endogenously over time. The existing literature often posits that workers vote deterministically for the political option that maximizes their value. In contrast, we show that allowing for a smoother voting hazard (Lindbeck and Weibull, 1987; Grossman and Helpman, 1996a; Dixit and Londregan, 1998; Matějka and Tabellini, 2021) is important to match the evidence of workers' voting behavior and quantify how the aggregate support for a transition changes over time.

2 Model

Time is continuous and periods are indexed by $t \geq 0$. Sectors or occupations are indexed by $i = 0, 1, 2, \ldots, I$.

2.1 Production

Final good. A representative firm produces the final good by combining the outputs of each sector i according to

$$Y_t = F\left(\{y_{i,t}\}_i\right), \tag{2.1}$$

where the sectoral outputs $y_{i,t}$ are complements in production. In turn, these sectoral outputs are produced either with domestic labor $l_{i,t} \geq 0$ or a labor-saving factor $k_{i,t} \geq 0$, i.e., foreign imports, automation, AI, according to

$$y_{i,t} = z_i \left[l_{i,t} + \gamma\left(i\right) k_{i,t}\right], \tag{2.2}$$

where the decreasing function $\gamma\left(i\right)$ captures the relative productivity of the labor-saving factor in each sector i and z_i is a sector-specific factor-neutral productivity. Sectors indexed by a low i, and hence a high γ, will be automated or offshored first. To fix ideas, we refer to $k_{i,t}$ as "automation" in this section.

Automation. In each period, a competitive firm uses units of final good ι_t to produce the labor-saving factor K_t according to

$$K_t = 1/q_t \times \iota_t, \tag{2.3}$$

where q_t captures the effective cost producing the labor-saving factor. In equilibrium, the amount of labor-saving factor produced is equal to the amount demanded across sectors

$$K_t = \sum_i k_{i,t} \tag{2.4}$$

This formulation can reflect either the production of robots or AI using domestic inputs (Guerreiro et al., 2022) or the country's trade balance as it exports ι_t and imports K_t in return at price q_t (Costinot and Werning, 2023).[1] The cost q_t falls exogenously over time due to technological improvements or increased trade integration, leading to a wider adoption of the labor-saving factor across sectors i.

[1] The stock of automation depreciates fully at the end of each period as in Guerreiro et al. (2022).

2.2 Workers

Preferences and demographics. Workers live for J years and are then replaced by a new cohort. Workers supply labor inelastically over their lifetime. and their preferences are given by

$$\int_0^J \exp\left(-\rho j\right) c_j dj \tag{2.5}$$

where c_j is consumption of the final good at age j and ρ is the discount rate. We assume that workers are risk-neutral or have access to perfect borrowing and saving, so they simply maximize the present discounted value of future earnings.

Skill accumulation. Workers' skills are determined in two phases: a specialization phase at birth where workers choose a sector or occupation $i^\star$ to specialize in, and a production phase where workers accumulate skills on-the-job.

In their specialization phase at birth, workers choose a *reference occupation* $i^\star$ which they are persistently attached to until they get displaced. Specifically, workers draw an innate ability $\theta \sim G$ at birth, with $\theta \in [0,1]$. Based on this ability, workers choose an occupation $i^\star \in [0,1]$ to specialize in and to start their career in ($i = i^\star$ when $j = 0$). Specializing in an occupation $i^\star$ carries a cost $\kappa\left(i^\star, \theta\right)$, and workers draw occupation-specific costs from independent extreme value type-I distributions. It is cheaper for a worker to specialize in an occupation that matches their innate ability θ, so $\mathbb{E}\left[\kappa\left(i^\star, \theta\right)\right] = 0$ if $i^\star = \theta$ and $\mathbb{E}\left[\kappa\left(i^\star, \theta\right)\right] > 0$ otherwise. A worker chooses the occupation $i^\star$ according to the hazard

$$f_t\left(i^\star, \theta\right) \propto \exp\left(\left\{W_t^{\text{new}}\left(i^\star\right) - \kappa\left(i^\star, \theta\right)\right\} / \xi\right), \tag{2.6}$$

where $W_t^{\text{new}}\left(i^\star\right)$ is a worker's continuation value at the start of their life if they begin their career in occupation $i^\star$ and ξ is the scale parameter that controls how elastic the specialization choice is to changes in the value of supplying labor in each occupation.

In their production phase when supplying labor, workers accumulate general and specific skills on-the-job as in Lise and Postel-Vinay (2020). The general skill applies to all occupations and accumulates exogenously at an age-specific rate η_j. In turn, workers accumulate two stocks of specific skills: one tied to their refer-

ence occupation $i^\star$, and one tied to all other occupations $i \neq i^\star$.[2] These stocks of specific skills accumulate at rate $\eta^+ > 0$ when the worker is employed in the corresponding occupation and at rate $\eta^- < 0$ otherwise. A worker who specializes in occupation $i^\star$ is endowed with a positive amount $\psi^{\text{endow}} \sim \Psi$ of specific skill in that occupation. We normalize the other stock to 1 at birth, without loss of generality. A worker's log-productivity in an occupation is the sum of their general skill and the specific skill that applies to that occupation.

A worker's productivity can be expressed as

$$h\left(j, \psi, i, i^\star\right) \equiv \exp\left(\chi_j + y\left(\psi, i, i^\star\right)\right), \tag{2.7}$$

where the life cycle component χ_j reflects their average log-productivity across occupations, and the occupation-specific component $y\left(\psi, i, i^\star\right)$ reflects their log-productivity difference across occupations. A worker's productivity in a given occupation grows at rate $\eta_j + \eta^+$ when they work there, and at rate $\eta_j + \eta^-$ if they are employed anywhere else. Therefore, their average log-productivity χ_j grows at rate $\eta_j + 1/2 \times (\eta^+ + \eta^-)$ and we normalize the initial level $\chi_0 \equiv 0$, without loss of generality. In turn, their relative log-productivity is

$$y\left(\psi, i, i^\star\right) \equiv \begin{cases} \psi & \text{if } i = i^\star \\ -\psi & \text{if } i \neq i^\star \end{cases}, \tag{2.8}$$

where the evolution of the state variable ψ depends on which occupation they supply labor to

$$d\psi_t = \eta\left(i, i^\star\right) dt \quad \text{with} \quad \eta\left(i, i^\star\right) = \begin{cases} 1/2 \times (\eta^+ - \eta^-) & \text{if } i = i^\star \\ -1/2 \times (\eta^+ - \eta^-) & \text{if } i \neq i^\star \end{cases}, \tag{2.9}$$

with $\psi_t \equiv \psi^{\text{endow}}$ at birth.

Labor reallocation. Workers are able to choose a new occupation at rate $\lambda > 0$, based on their productivity (2.7) in that occupation. Their reallocation is partially directed across occupations, which allows to model to generate gross flows across

[2] To keep our state space manageable, we do not keep track of separate stock of specific human capital in each occupation $i \neq i^\star$.

occupations. Specifically, a worker who is able to reallocate and currently supplies labor to occupation i chooses occupation i' with probability

$$p_t\left(i';j,\psi,i,i^\star\right) \propto \exp\left(W_t\left(j,\psi,i',i^\star\right)/\zeta\right), \tag{2.10}$$

where $W_t\left(j,\psi,i,i^\star\right)$ is the continuation value of a worker of age j, with relative skill ψ, who supplies labor to occupation i and specialized originally in occupation $i^\star$.[3] In turn, the scale parameter ζ controls the elasticity of the reallocation choice with respect to changes in the value of supplying labor in each occupation. The reallocation is purely directed in the limit $\zeta \to 0$ and purely random in the limit $\zeta \to \infty$. As usual, the reallocation hazard (2.10) can be microfounded by introducing amenity shocks distributed according to independent extreme value type-I distributions or information acquisition costs.[4]

2.3 Markets and Equilibrium

All markets are perfectly competitive. In particular, workers are paid their marginal product. All firms operate technologies with constant returns to scale so there are no profits. A competitive equilibrium is defined as usual.

2.4 The Transition and its Political Economy

Transition. The economy initially rests on its stationary equilibrium where q_t is fixed at some value $q > 0$. The transition begins in period $t = 0$ due to an unanticipated change in q_t, which then decreases over time. Workers have perfect foresight from $t = 0$ onward.

Political economy. At any point in time, workers are given the opportunity to vote on two options: either maintaining the status quo transition, or rolling back the transition and reverting q_t back to the original steady state q. Of course, workers' idiosyncratic states have evolved over time and will *not* revert immediately back to what they would have been had the transition never taken place. Workers' vote

[3] In particular, $W_t^{\text{new}}\left(i^\star\right) \equiv \int W_t\left(0,\psi^{\text{endow}},i^\star,i^\star\right) d\Psi$ in expression (2.6).

[4] Amenity values would raise a workers' value, whereas information acquisition costs would decrease it. We thus follow Traiberman (2020) and Lentz et al. (2026) and do not include these amenity values or information costs in workers' values.

has a random component, reflecting idiosyncratic reasons why they prefer one option over the other or rational inattention (Lindbeck and Weibull, 1987; Grossman and Helpman, 1996a; Dixit and Londregan, 1998; Matějka and Tabellini, 2021). Specifically, the probability that a worker votes to maintain the status quo is

$$\mathcal{S}_t\left(j,\psi,i,i^\star\right)=\mathcal{F}\left(\frac{W_t\left(j,\psi,i,i^\star\right)}{W_t^{\text{undo}}\left(j,\psi,i,i^\star\right)}\right), \tag{2.11}$$

where the hazard function $\mathcal{F}$ is a increasing function between 0 and 1 and the value function $W_t^{\text{undo}}\left(j,\psi,i,i^\star\right)$ is the one that prevailed at the original steady state but evaluated at the worker's current states. Finally, the share of workers who support the status quo is

$$\mathcal{S}_t^{\text{agg}}=\int \mathcal{S}_t\left(j,\psi,i,i^\star\right)d\mu_t\left(j,\psi,i,i^\star\right), \tag{2.12}$$

where μ_t is the distribution of workers' states.

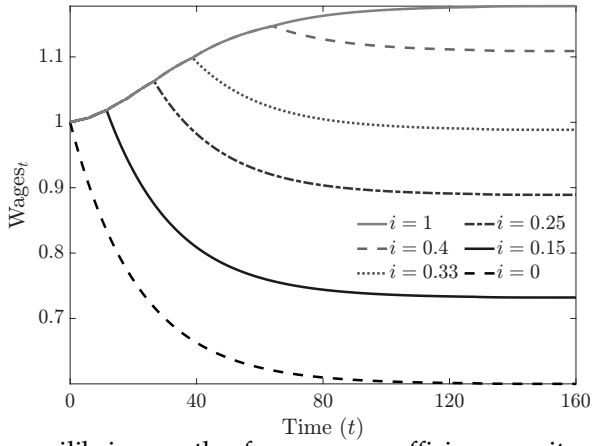
3 Conceptual Insights

This section describes the conceptual insights our model delivers. To build intuition, this section considers a limit of our model in which workers may freely reallocate sectors at every instant and reallocation is perfectly directed: $\lambda\to\infty$ and $\xi\to 0$. We begin by showing that workers earnings – and thus value of maintaining the status quo rather than undoing the transition – follow a wave-shaped pattern: they first rise, then fall before rising again. We then show the importance of endogenous skill accumulation for the timing and amplitude of these waves. Finally, we illustrate how different assumptions around the shape of the voting function translate into aggregate support for undoing the transition. For concreteneess and with an eye to our empirical application to trade, we refer to the competing factor of production as foreign or imported goods and use the word "offshoring" to refer to production using the competing factor rather than domestic labor.

3.1 A Wave Pattern in Earnings

To build intuition, let us momentarily abstract from an endogenous evolution of the skill distribution – that is, skills do not accumulate on the job ($\eta=0$) and

Figure 3.1: Sectoral wages $w_t(i)$ along the transition



Notes: This figure plots the equilibrium path of wages per efficiency unit under the status quo transition, for various sectors i. High i sectors have the lowest $\gamma(i)$ and hence are the least exposed to the decline in q_t.

specializations cannot be changed after birth ($\kappa = \infty$). Workers earnings in each sector i are thus determined entirely by the skill price $w_t(i)$ and their relative skill endowment $\psi_0 = \psi^{\text{endow}}$.

We begin by analyzing the dynamics of skill prices $w_t(i)$. Firms in sector i face a choice of whether to produce using labor or the foreign good. Since the physical productivity of labor is 1, the marginal cost of producing with labor is simply the wage $w_t(i)$. Meanwhile, the marginal cost of producing with capital is $q_t/\gamma(i)$: each unit of $k_t(i)$ must be paid q_t units of the final good and produces $\gamma(i)$ units of good i. Therefore, the marginal cost of production in i is the lesser of the wage $w_t(i)$ and $q_t/\gamma(i)$.

Since all markets are competitive, the equilibrium price of each good is equal to its marginal cost and workers are paid their marginal revenue product. Since one unit of labor produces one unit of sector i's output, the marginal revenue product of labor is always equal to the equilibrium price of each good, denominated in units of the final numeraire consumption good.

Figure 3.1 plots the evolution of sectoral wages $w_t(i)$ over time for a variety of sectors i. Consider first the dashed black line, which represents the sector in which domestic labor has the weakest comparative advantage $i = 0$. Workers in this sector are displaced by the foreign goods as soon as the transition begins. The cost of producing in this sector declines over time reflecting the declining cost of imported goods q_t. Therefore, the wage paid to workers in that sector must also

equal $w_t(0) = q_t/\gamma(0)$ which falls gradually over time.

Now examine the solid gray line corresponding to the sector in which the domestic labor has the strongest comparative advantage: $i = 1$. This sector always produces using domestic labor, and is never displaced by the competing factor. In this sector, wages rise over time reflecting the fact that output from other complementary sectors is now lower priced. In effect, the final good becomes cheaper to produce, so workers employed in $i = 1$ benefit from cheaper consumption goods over time so that their real wage increases.

The other lines of Figure 3.1 plot the evolution of $w_t(i)$ for several other intermediate sectors. Early in the transition, these sectors behave the same as $i = 1$: workers in these sectors benefit from cheaper consumption goods and so see rising real wages. Eventually, however, the decline in q_t is sufficient that $q_t/\gamma(i) \leq w_t(i)$. At this stage, producing using domestic labor is no longer cheaper than producing with imports, and wages in that sector begin to decline along with the path of q_t. As a result, the price of labor in these moderately-exposed sectors follows an inverted-V shape.

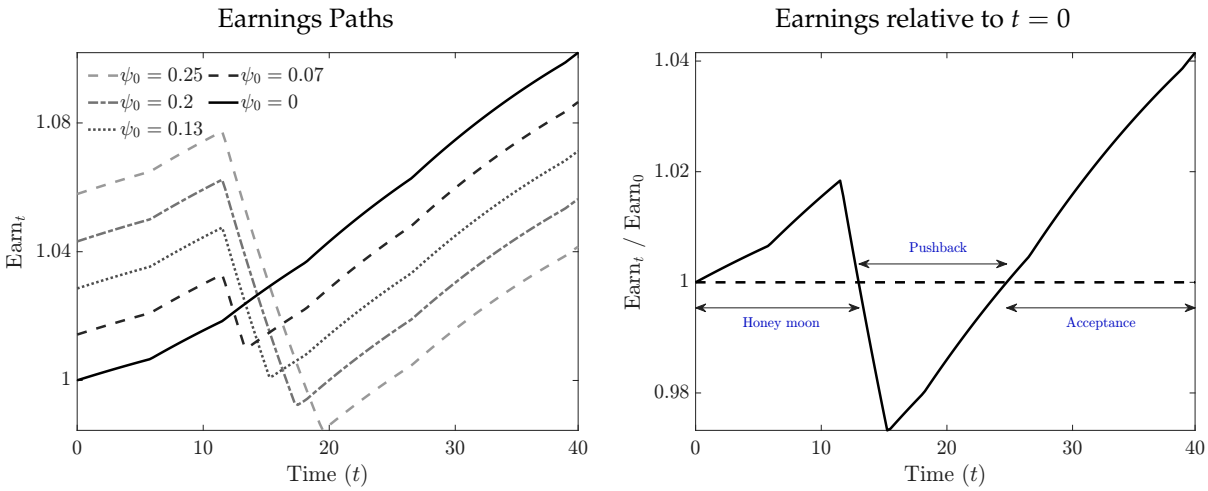
The interaction of these inverted-V shapes with worker reallocation generates wave-shaped earnings paths. In this simplified model without skill accumulation, workers choose which sector to work in at every instant according to

$$\max\left\{w_t(i^\star)\exp\left(\chi_j + \psi_0\right), \max_{i\neq i^\star} w_t(i)\exp\left(\chi_j - \psi_0\right)\right\}, \tag{3.1}$$

that is, they maximize their static income each period, accounting for the price of skill in each sector and their relative skills. Problem 3.1 implies that if wages fall too far in a worker's sector of specialization, they will eventually switch to another sector with higher wages, forfeiting their specific skill.

The resulting earnings paths are depicted in Figure 3.2. The left panel reports the path of earnings for workers with different levels of specific skill ψ_0 with specialization in some $i^\star$ which is partially exposed to the transition (an intermediate $\gamma(i)$). The solid black line depicts a worker with no specific skill: $\psi_0 = 0$. This worker faces no cost of switching sectors as they forgo no specific human capital. Their earnings are thus the upper envelope of $w_t(i)$ in this model without skill accumulation, which follows the path of wages in the least exposed sector $w_t(1)$. Workers with perfectly transferable skills therefore see steady wage increases over

Figure 3.2: Earnings Paths $w_t(i)$



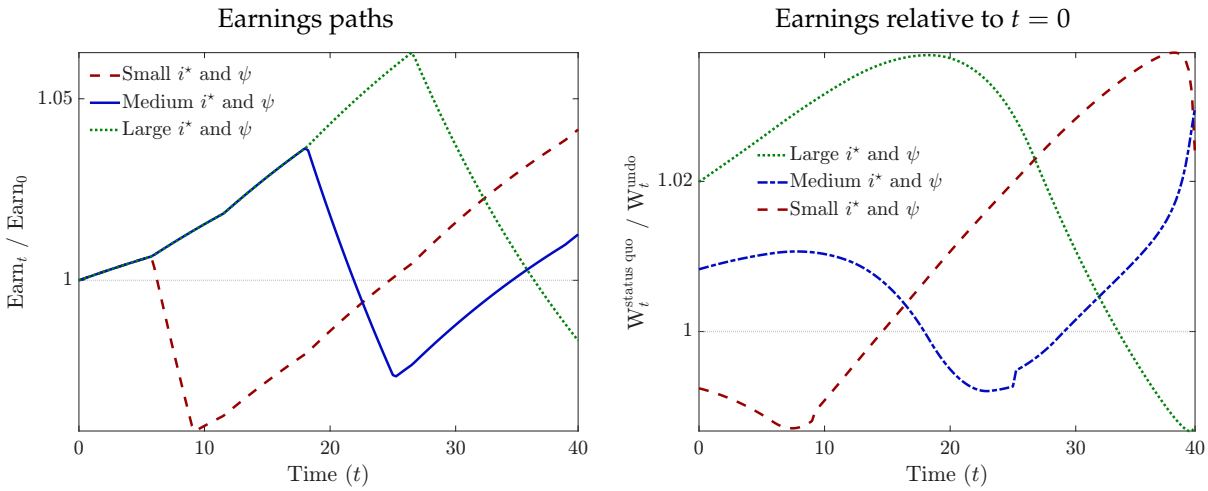
Notes: The left panel plots the path of earnings under the status quo transition for workers who specialized in a partially exposed sector ($i^\star = 0.33$) and for various levels of initial specific skill ψ_0. We abstract from skill accumulation at this point. The right panel plots earnings for a particular worker type relative to the earnings in period 0.

time. Such workers always benefit from the status quo transition.

Workers with higher relative skill ψ_0 initially have higher earnings in the reference sector $i^\star$ reflecting their higher skill there. Their wages also initially increase following the path of $w_t(i)$. However, when sector $i^\star$ begins to be offshored and wages decline following the path depicted in Figure 3.1, workers with more specific skills do not immediately switch to unexposed sectors since it is not worthwhile to forgo their skills. Thus, these workers earnings begin to decline over time, potentially to a level below their earnings in the initial steady state. Once the wage declines sufficiently in the reference sector, these workers "bite the bullet" and switch to an unexposed sector, and their earnings rise again. Those with stronger comparative advantage in their reference sector $i^\star$ will have higher earnings early in the transition, but larger losses later in the transition.

The right panel of Figure 3.2 reports earnings relative to the initial steady state for workers. One can readily see three phases on this plot. First, there is the *honeymoon* phase in which workers benefit from the transition through cheaper consumption goods. After their job is offshored, the worker experiences a *backlash* phase in which earnings fall below their initial steady state level. Then, a sufficient amount of time after switching out of the declining sector, the decline in the price of consumption goods is sufficiently large for the worker to benefit again relative

Figure 3.3: Earnings and Value Paths for Different $i^\star$ and ψ_0



Notes: The left panel plots earnings paths under the status quo transition for workers who specialized in different sectors $i^\star$ and have different specific skill levels ψ . These earnings are expressed relative to their initial earnings in $t = 0$. The right panel plots the continuation values under the status quo for the same workers, relative to the continuation value of undoing the transition and setting $q_t = q$.

to the initial steady state, leading to the *acceptance* phase.

Figure 3.3 reports this pattern for a variety of sectors of specialization $i^\star$ and degree of specific skills ψ_0. The left panel report earnings while the right panel reports workers' continuation values. The figure clarifies that workers with expertise in unexposed sectors (green dotted line) remain in the honeymoon phase for longer, and experience the backlash later, than do workers with expertise in highly exposed sectors. However, over time, the identity of those who benefit or are hurt most by the transition flips – while, those with limited expertise in the most exposed sectors (low $i^\star$, black dashed line) lose the most in the short run from the status quo transition, they benefit the most in the long run since they switch soonest and have the smallest loss of skills. Continuation values inherit the same shape as the earnings paths, but are naturally smoothed by the fact that they are forward-looking.

The key takeaway of this section is that workers' income – and thus their support for maintaining the status quo transition rather than undoing the transition – follows a wave-shaped pattern: it rises during a honeymoon phase, then declines in a backlash phase, before finally rising again after workers switch sectors in an acceptance phase. An implication of this pattern is that the backlash to sectoral

transitions will tend to be finite-lived. As a result, it will eventually become politically *too late to undo* a sectoral transition by, for instance, rolling back globalization or appealing to Luddite tendencies. Once enough workers have moved on from the declining industry, they may not support its reinstatement. As we will see in section 4, this wave pattern is visible in polling data on trade. Note that this conclusion is insensitive to workers' information about the future path of q_t, as they make only static decisions in this simplified model without skill accumulation.

3.2 The Role of Skill Accumulation

The above section relied on a stylized model without skill accumulation to build intuition for the core economics. We now argue that skill accumulation is an important determinant of the timing and amplitude of the wave pattern.

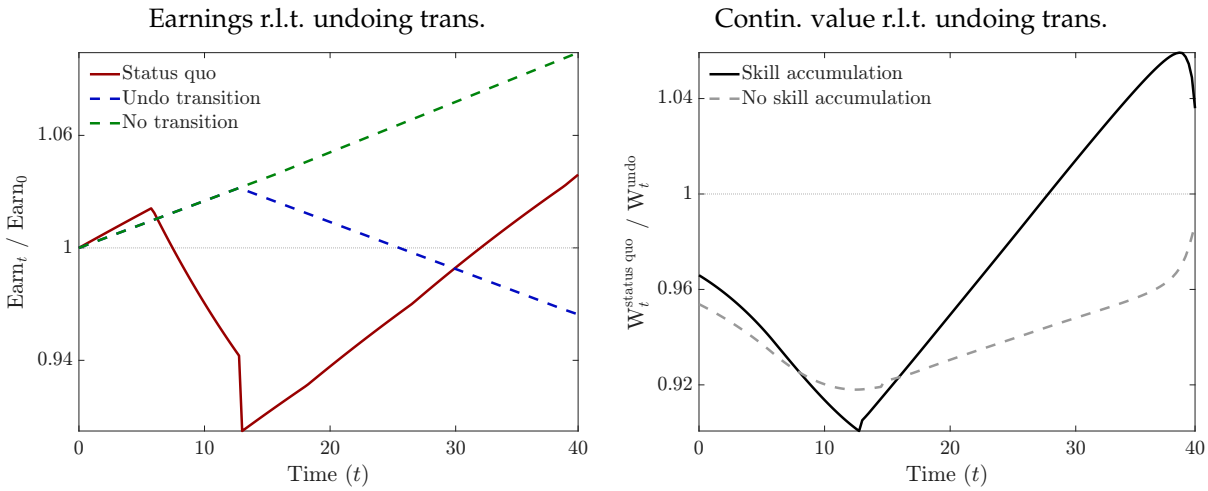
To explain how skill accumulation changes the conclusions above, Figure 3.4 plots the path of earnings for a worker with moderate expertise in an intermediate $i^\star$. The green dashed line reports the worker's earnings were there no transition at all. In this case, skill prices remain fixed at their steady state level $w_t(i) = w_0(i)$ and the worker has no reason to switch sector. However, their wages rise at a constant rate reflecting skill accumulation.

The solid black line depicts the workers earnings under the status quo transition. For simplicity and to isolate the role of skill accumulation, we assume the path of wages $w_t(i)$ follows the same path as would hold in the model without skill accumulation depicted in Figure 3.1 throughout this section.[5] At first, earnings grow faster under the status quo transition than in the scenario without any transition; this reflects the fact that the worker accumulates skills (as in the green line) *and* the price of labor $w_t(i)$ rises. But once the occupation becomes partially automated, the worker's earnings decline following the path of $w_t(i)$, albeit slower than if their skills were not also accumulating in this sector.

With skill accumulation, occupation switching decisions become forward-looking: a choice of occupation is effectively an investment in skills in that occupation. As a result, when the wage falls sufficiently in the worker's sector of expertise, the worker will switch to a different sector even if doing so entails a discrete drop in their earnings, as is visible in the figure. Their earnings then rise again in the new

[5] We therefore abstract from additional general equilibrium forces from skill accumulation operating through the effect on wages.

Figure 3.4: The role of skill accumulation



Notes: The left panel plots a worker's earnings over time under three transition scenarios. The green dashed line corresponds to the scenario where there is no transition at all. The solid curve corresponds to the case in which the status quo transition continues forever. The blue dashed curve corresponds to a workers' earnings in period t if were the transition were be undone from date t onwards. The right panel plots the corresponding continuation value of maintaining the status quo transition, relative to undoing the transition. The black line corresponds to the model with skill accumulation, while the gray line represents the model without skill accumulation.

sector, reflecting both the path of skill prices and the accumulation of skills in the destination sector.

The blue dashed line depicts the earnings the worker would realize if the transition were undone in period t. Undoing the transition reverts all $w_t(i)$ back to their steady state level, but crucially does not affect workers' skills directly. Before the worker switches sectors, the earnings they receive from undoing the transition overlap exactly with the earnings they would receive if there were no transition at all because they only accumulate skills in their reference sector $i^\star$.

However, after they leave the declining sector and switch to an unexposed sector, the worker begins accumulating skills which are specific to the *unexposed* sector, while their skills in their old sector begin to depreciate. The depreciation of skills in the declining sector implies that their earnings if they were to return to the old sector would be lower than they were before, even if the transition were undone and wages were reverted. The blue line depicts this pattern: the longer the worker has been away from the old sector, the lower will be their earnings if the transition were reverted and they were "forced" to return to the declining sector.

The key determinant of political support is the comparison of the earnings

paths obtained under the status quo transition (solid black) versus the path obtained if the transition were undone (blue dashed). Therefore, even workers who may be harmed by the transition relative to a scenario without the transition at all, may still oppose undoing the transition.

The additional forces introduced by skill accumulation can flip whether a worker prefers undoing the transition. The right panel of Figure 3.4 plots the relative continuation value from maintaining the status quo relative to the continuation value of undoing the transition for the model with skill accumulation (solid black line) and without skill accumulation (dashed gray line) for a worker with specific skills in a heavily exposed sector (low $i^\star$). Since this worker is tied to a declining sector, the value of the status quo relative to undoing the transition is below 1 early in the transition in both models: they would initially prefer to undo the transition. The worker eventually switches i and the relative value of the status quo transition rises. But the initial decline and subsequent rise in the relative value of the status quo transition is significantly steeper in the model with skill accumulation because the value of reverting to the old sector declines as the worker's skills there depreciate. The steeper rise in support for the status quo transition is large enough that the worker's labor market value from maintaining the status quo is eventually higher than their value of undoing the transition with skill accumulation, while the reverse is true without skill accumulation.

In sum, skill accumulation is an important determinant of the timing and size of support of the wave pattern of support. Skill accumulation and depreciation effectively introduces a cost to workers of reverting back to their old sector that grows over time. Intuitively, if a toy manufacturer loses his job to globalization but spends 20 years outside of the industry, they will not be as productive in their old toy manufacturing job even if trade barriers were erected to reshore the industry.

One final observation is warranted. As workers approach the end of life, the relative value of the status quo converges to 1 in both models. This reflects the fact that older workers have less time in the labor market before retirement, shrinking workers' continuation value regardless of whether the transition is maintained or undone. This life cycle force suggests that older and younger workers will have different intensities of support for undoing the transition. Whether this intensity of support matters depends on the shape of the voting hazard, to which we now turn.

3.3 Aggregate Support and the Shape of the Voting Function

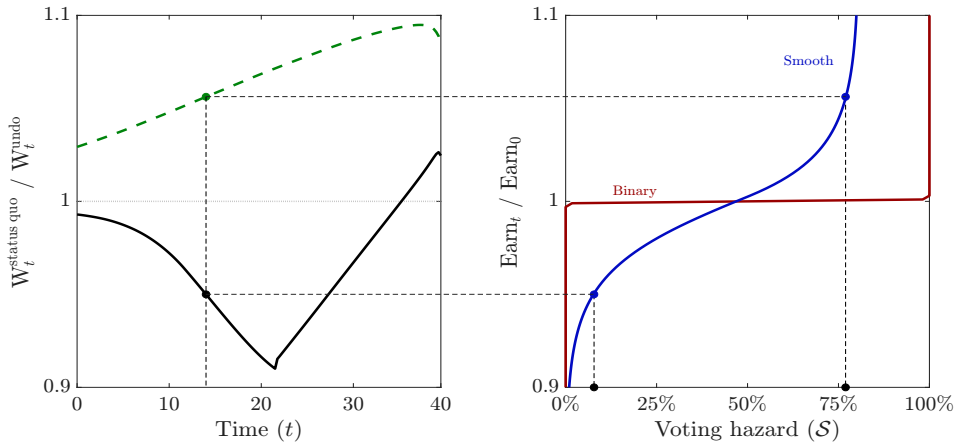
Thus far, we have demonstrated a wave pattern of support at the individual level that depends on the degree of skill accumulation. How these micro patterns of support translate into aggregate support for the transition is determined by the shape of the voting hazard $\mathcal{F}\left(W^{\text{status quo}}/W^{\text{undo}}\right)$.

To see how the voting function matters, Figure 3.5 illustrates two particular voting functions. The first one, depicted by the solid line on the right plot, is a binary voting hazard. It assumes that people will vote with 100% probability for the option that provides them the highest continuation value: that is, they vote for maintaining the status quo if and only if $W_t^{\text{status quo}} \geq W_t^{\text{undo}}$. This is a natural benchmark used in Mayer (1984); Fernández and Rodrik (1991); Hassler et al. (2003). In contrast, the blue line depicts a smoother voting hazard, in which workers are more likely to vote for maintaining the status quo the more that they benefit from it. Such a smooth voting hazard can be rationalized through idiosyncratic preferences for reverting the transition which may relate to, for instance, identity, party preferences, or community behavior (Lindbeck and Weibull, 1987; Persson and Tabellini, 2000; Shayo, 2009; Bonomi et al., 2021; Grossman and Helpman, 2021). Existing empirical work suggests that voters may be more responsive to losses than to gains (Bloom and Price, 1975; Alesina and Passarelli, 2019), and we thus consider this asymmetry in this section.

To understand how these two voting hazards can generate radically different aggregate support for maintaining the transition, consider the following simple example with two types of worker whose continuation values are depicted in the left panel of Figure 3.5. Worker type 1 has expertise in an unexposed sector (high $i^\star$) and has relative values given by the green curve. This worker always has higher continuation value under the status quo transition than from undoing the transition. Worker type 2 has expertise in an exposed sector (low $i^\star$) and has relative values given by the black curve: their value of maintaining the trnasition declines before rising after switching.

Figure 3.6 plots aggregate support for maintaining the status quo transition rather than undoing the transitions under the assumption that worker 1 constitutes 55% of the population. The left panel plots support for the transition with a binary voting hazard. Since worker 1 always has higher value from maintaining the status quo and are a majority of the population, a majority of workers would vote to

Figure 3.5: Voting Hazards $\mathcal{F}\left(W_t / W^{\text{undo}}\right)$



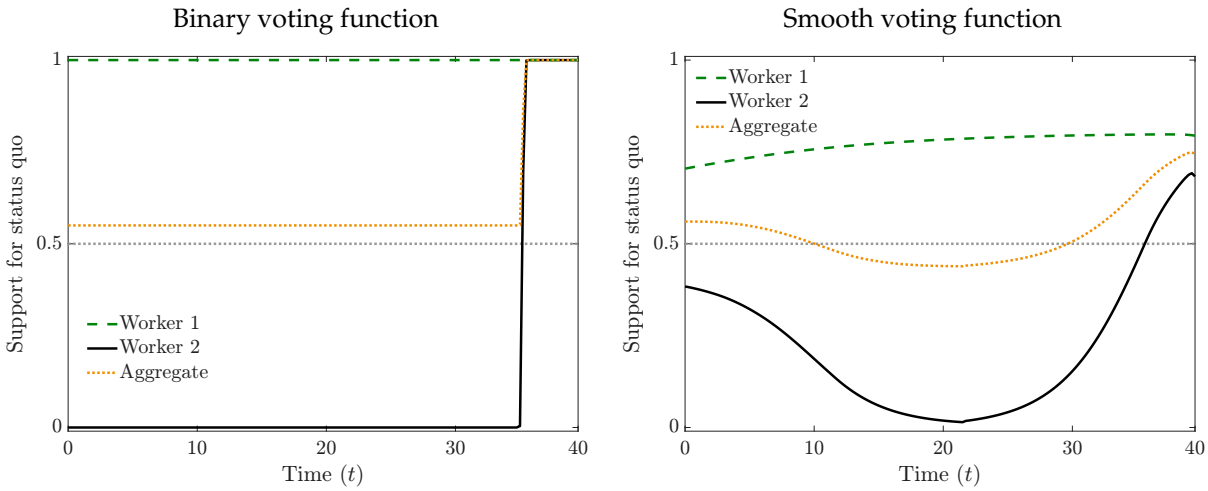
Notes: The left panel plots two workers' continuation values in various period t along the status quo transition, relative to the continuation value when undoing the transition in period t. The green dashed curve corresponds to a worker who specialized in a sector unexposed to automation or trade (high $i^\star$) while the black line corresponds to a worker in a heavily exposed sector (low $i^\star$). The right panel illustrates two voting hazards. The black line corresponds to a binary hazard in which a worker votes with certainty for the option that maximizes their continuation value. The blue line corresponds to a smoother voting hazard in which the worker is more likely to vote for the option that maximizes their continuation value.

maintain the status quo transition under this binary hazard. Aggregate support in this case exhibits no wave pattern.

In contrast, the right panel of Figure 3.6 reports aggregate support under the smooth asymmetric voting function. Here, a majority of type 1 workers vote to maintain the transition and a majority of type 2 workers vote to undo the transition for much of the transition's early phase. However, given voting responds to the intensity of continuation value losses, the decline in support for type 2 workers is larger than the rise in support among type 1 workers. Therefore, the aggregate support follows the wave pattern described above – it begins above 50%, then declines below 50%, before again rising so that a majority of workers support maintaining the status quo transition.

The drastic difference between these two voting functions highlights the importance of $\mathcal{F}(\cdot)$ for the political economy of sectoral shifts. We make some progress towards measuring this function below. Note that the smooth voting function is, in some sense, flatter than the binary voting function, which exhibits a discontinuous jump in voting probabilities. A key takeaway of this section is that a flatter voting function can, in fact, generate more pronounced wave patterns of support.

Figure 3.6: The role of the voting function for aggregate support



Notes: This figure shows how the shape of the voting hazard affects aggregate support for maintaining the status quo transition. The left panel considers a binary voting hazard, so workers vote with certainty to maintain the status quo transition if they benefit from it. The right panel considers a smooth voting function, so workers are more likely to vote to maintain the status quo transition if they win more from it. The solid black and green dashed lines report the voting probability of two types of workers, who correspond to those depicted in the left panel of Figure 3.5. The orange dotted line plots the aggregate support which average over the two worker types (worker type 1 constitute 55% of the population).

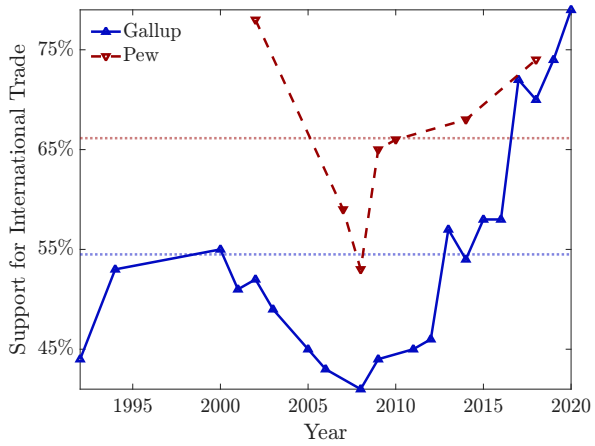
4 Empirical Evidence from Polling Data

To provide evidence for the wave pattern of support discussed above, one requires a long time series of opinions about a sectoral shift. We therefore turn to data from opinion polls. It is generally difficult to compare responses across different polls, either because they word questions differently or have different sampling frames. Therefore, a systematic review of multiple sectoral transitions is impossible.

However, there are a set of questions related to trade that have been consistently asked by major US polling outlets that we might exploit. Specifically, Gallup's World Affairs poll has asked "Do you see foreign trade more as an *opportunity* for economic growth through US exports or a *threat* to the economy from foreign imports?" periodically back to 1994. The World Affairs poll has maintained a consistent sampling frame over the past 30 years and thus provides a unique opportunity to examine the wave pattern our model predicts.

Likewise, since 2002, the Pew Global Attitudes poll has asked "What do you think about the growing trade and business ties between US and other countries

Figure 4.1: Evidence for Wave from Polling Data



Notes: This figure reports the share of respondents who state that they support international trade in polls by Gallup (blue solid curve) and Pew (red dashedcurve) asking consistent questions over time. The Gallup question is "Do you see foreign trade more as an opportunity for economic growth through US exports or a threat to the economy from foreign imports?," and the blue curve plots the share who report that it is an opportunity for growth. The Pew question is "What do you think about the growing trade and business ties between US and other countries for our country?," and the red curve plots the share of respondents who answered "good" or "very good."

for our country?" with multiple choice options "very good," "good," "bad," or "very bad." While this poll has a shorter time frame, it provides a useful validation of the patterns found in the Gallup World Affairs poll.

Figure 4.1 plots the share of respondents who support trade in these polls over time. The blue line reports the share of respondents in the Gallup poll who report that trade is more of an opportunity for growth. A wave pattern can be clearly observed in the Gallup data. More and more respondents report that trade is an opportunity over time, which our theory suggests reflects the cheaper consumption goods available. Then, beginning in 2000 with the famous "China shock," support began to steadily decline, reflecting the backlash from lost labor income our model would predict. Finally, support starts to rise steadily again, as our model would predict when workers move on from the declining industries and acquire skills in other industries. Overall, the Gallup data confirms the wave pattern predicted by our model.

The red line reports the share of respondents in the Pew poll that state that trade is "very good" or "good" for the US. Although these data do not go far enough back to see the initial rise in support during the 1990s, the patterns are very consistent with the Gallup poll when there is overlap. Support for trade declines in the

Pew poll during the China shock, and then rises during the acceptance phase, with the timing of this rise coinciding exactly with the timing of the rise in the Gallup data.

5 Quantitative Application to Trade

This section explores the quantitative implications of the model in an application to trade. We have two goals with the quantitative model. First, we wish to study whether counterfactual tax and transfer policies may have been able to increase political support for maintaining the status quo transition or influence the observed wave pattern of support. Finally, we use the model to forecast the political impact of a potential China Shock 2.0 which some observers have referenced in recent media (Autor and Hanson, 2025).

5.1 Quantitative Extensions

While the model of section 2 delivers clean conceptual insights, it is ill-suited for quantitative analysis for four reasons. First, workers may freely reallocate at every instant in that model, which removes any sense in which a worker may be "trapped" in a declining industry. Second, it abstracted from the large gross flows that are in the data, with many workers flowing both in and out of trade-exposed sectors. Third, it assumed away the possibility that workers may leave the labor force in response to the shock, while the empirical literature has found workers exposed to trade shocks often left the labor force to, for instance, receive disability benefits (Autor et al., 2013). Finally, the model did not feature any tax and transfer scheme which may insure workers from these shifts. We therefore augment the model for the quantitative analysis as follows. Additional details are provided in Appendix A.

Reallocation. Workers now have an opportunity to switch across sectors with Poisson arrival rate λ. When a reallocation opportunity occurs, workers engage in a noisy reallocation process that takes a nested logit form. We explain this in two steps. First, suppose a worker has decided to leave their current job i. The probability that such a worker chooses a specific i', given that they have decided to leave

i is assumed to be

$$\tilde{p}_t\left(i', i; j, \psi, i^\star\right) = \frac{\exp\left(W_t\left(i', i^\star, \psi, j\right)/\underline{\zeta}\right)}{\sum_{\tilde{i}\neq i}\exp\left(W_t\left(\tilde{i}, i^\star, \psi, j\right)/\underline{\zeta}\right)}.$$

The parameter $\underline{\zeta}$ thus determines the cross-sector labor supply elasticity among movers. We allow for the possibility that workers may be less elastic to leaving their current sector. To do so, first define the expected value of leaving one's current occupation as

$$\bar{W}_t\left(-i; i^\star, \psi, j\right) = \sum_{i'\neq i}\tilde{p}_t\left(i', i; j, \psi, i^\star\right) W_t\left(i', i^\star, \psi, j\right).$$

Then the probability a worker chooses to stay in their current occupation is given by

$$p_t\left(i, i; j, \psi, i^\star\right) = \frac{\exp\left(W_t\left(i, i^\star, \psi, j\right)/\bar{\zeta}\right)}{\exp\left(\bar{W}_t\left(-i; i^\star, \psi, j\right)/\bar{\zeta}\right) + \exp\left(W_t\left(N, i^\star, \psi, j\right)/\bar{\zeta}\right) + \exp\left(W_t\left(i, i^\star, \psi, j\right)/\bar{\zeta}\right)}.$$

where $W_t\left(N, i^\star, \psi, j\right)$ is the worker's value if they leave the labor force, to be described below. Thus the parameter $\bar{\zeta}$ governs how responsive job-switching is the decline in value in one's current occupation. By Bayes rule, the unconditional probability of switching from i to $i' \neq i$ when a reallocation opportunity arrives is thus $\left(1 - p_t\left(i, i; j, \psi, i^\star\right)\right) \cdot \tilde{p}_t\left(i', i; j, \psi, i^\star\right)$.

One can rationalize these functional form either by assuming workers draw i.i.d. idiosyncratic amenities for jobs from a nested Frechet distribution, or by assuming information acquisition costs as in (Matějka and McKay, 2015).

Labor Force Participation. We assume that workers who receive a reallocation opportunity may always choose to leave the labor force rather than work in a market production. We denote this as workers choosing $i = N$ for "not in labor force." Such workers receive a constant flow benefit b^N capturing home production, but do not accumulate any further skills. Workers outside of the labor force receive an opportunity to rejoin the labor force at rate λ^N, and they choose which i to work at (if any) following the decision problem outlined above.

Tax System. We parameterize a tax and transfer system as in Bénabou (2002); Heathcote et al. (2017). Specifically, the pre-tax wage rate per efficiency unit in occupation i (that firms pay) remains $w_t(i)$ and workers' pre-tax earnings remain $w_t(i) h(i, i^\star; \psi, j)$. But workers' post-tax earnings – which enters their values – is given by

$$y^{post}(i, i^\star; \psi, j) = (1 - \tau_0)(w_t(i) h(i, i^\star; \psi, j))^{1-\tau_1}.$$

The parameter τ_0 governs the level of taxes, while τ_1 affects tax progressivity. If $\tau_1 = 0$, all households face the same tax rate, while if $\tau_1 = 1$, all workers receive the same post-tax income regardless of their pre-tax earnings.

5.2 Calibration

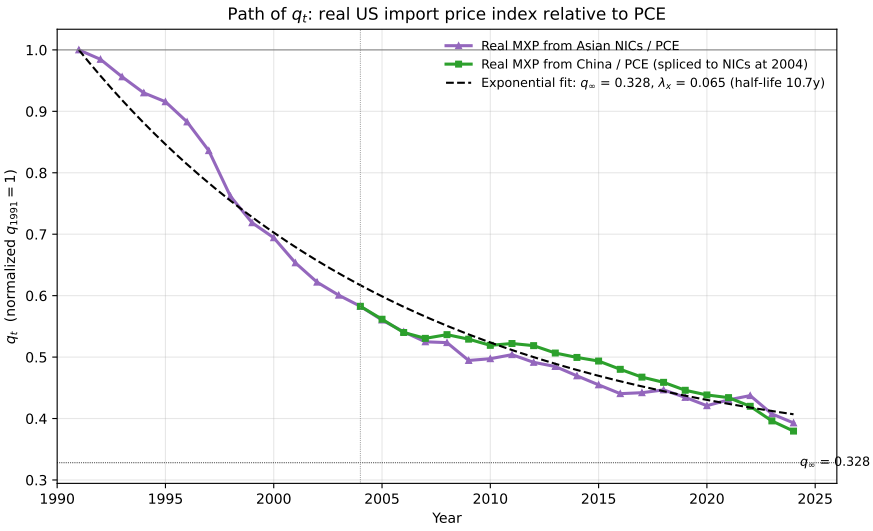
5.2.1 Calibrating the Economic Block

Path of q_t. In a trade application, the price of the new technology represents the real price of imports. We thus take q_t to be the US import-price index from the Asian Newly Industrialized Countries provided by the Bureau of Labor Statistics (BLS), deflated by the aggregate US PCE deflator. We normalize $q_{1991} = 1$. We plot the implied path of q_t in Figure (5.1). The blue line is the raw real import price index, while the dashed line is a fitted exponential curve, which we use as our path of q_t. The BLS published an analogous real-import-price index for China alone beginning in 2004, which we plot in green. The two series track within around 1pp from 2004 forward. The exponential curve implies a long run decline in the relative price of imports of 67.2%, with a half-life of convergence of 10.7 years.

Defining Trade Exposure. An important challenge for a quantitative exercise is to define what each sector i represents in the data. To this end, we exploit the feature of our model that the share of value added produced abroad rather than using domestic labor is directly related to the $\gamma(i)$ schedule. In particular, low i sectors that are highly exposed to the trade shock will have higher import penetration ratios which begin their rise sooner than high i sectors. For instance, there will be no import penetration if $\gamma(i) = 0$, but import penetration will reach 50% relatively quickly if $\gamma(i)$ is much larger than one. We therefore rank sectors according to their measured import penetration ratios.

We use information on shipments and sales from the BEA's Input-Output (I-

Figure 5.1: The path of q_t in trade application



Notes: This figure plots the estimated path of q_t in our trade application. The blue line reports the real import price index from Asian countries over time, while the green line reports the real import price series from Chinese goods. These series come from the BLS and are normalized to 1 in the year 1990. Price indices are deflated by the PCE price deflator. The dashed black line represents the curve with exponential decay that fits these series.

O) tables from 1997-2016. We define import penetration (IP) ratios as the ratio of imports to the sum of imports and sales.[6] This is available for all sectors. The distribution of IP ratios shifts to the right over time as the model would predict, as we show in Appendix Figure (C.1). In our baseline analysis, we rank sectors according to the highest IP ratio obtained in-sample. By this methodology, the most trade-exposed sectors are apparel, footwear, toy, audio-video equipment and electronic computer manufacturing sectors, while service sectors are largely non-exposed.

We provide more detail and robustness to this classification system in Appendix (C). We show that rankings are highly correlated across a variety of classification mechanisms which rank sectors according to either 1) the IP ratio at the end of the sample, 2) the time their IP ratio is projected to cross a certain threshold X, for a variety of X and projection methods. All such rankings provide similar results.

[6] An alternative would be to define IP as the ratio of imports to the sum of imports and sales *net of exports*. This option has the interpretation of providing the share of domestic consumption that is provided by foreign imports. However, what matters for labor demand is the extent to which total *production* of a sector is moved abroad, rather than total consumption.

External Calibration. We calibrate the working lives of workers to last $J = 40$ years and suppose a discount rate of 0.03. For our baseline analysis, we study the case in which different jobs are combined using a Cobb-Douglas production function so that the elasticity of substitution between i is 1, and explore sensitivity to this choice below.

Table 5.1: Calibration

Parameter	**Description**	**Value**	**Source/Target**
External			
J	Lifespan	40	Career length
ρ	Discount rate	0.03	3% interest rate
ϕ	Elast. of Subs. btwn i	1	Cobb-Douglas
χ_j	Age-skill Profile	—	Reg. $\Delta \ln w$ on age FE & tenure (PSID)
η	Specific skill accum.	0.034	Reg. $\Delta \ln w$ on age FE & tenure (PSID)
μ_{ψ_0}	Mean of initial ψ_0	0.350	Mean earn. drop across i at 25 (CPS DWS)
σ_{ψ_0}	SD of initial ψ_0	0.244	S.D. earnings drop (CPS DWS)
κ	Specialization fixed cost	4	Cost of college/average income
ξ	Specialization choice scale	16.8	Smeets et al. (2026)
ν	Voting function parameter	0.67	Trump vote share response to trade
Internal			
$G(\theta)$	Innate talent distribution	—	Employment in sector i in 1980
z_i	Sector i Productivity	—	Average wages in sector i in 1980
$\gamma(i)$	Comp. Adv. Schedule	—	Employment in sector i in 2025
λ	Reallocation opp. arrival	TBD	95% reallocation within 8 years
ζ	Cross-i LS elasticity	TBD	Labor supply elasticity = 2
$\bar{\bar{\zeta}}$	Elasticity of job leaving	TBD	Quarterly sectoral gross flows = 5.44%

The structure of our model allows us to calibrate a number of additional parameter to directly match features of the data. To recover the parameters governing the skill distribution, we note that log earnings in our model are given by

$$\ln y_t^{pre}(i, i^\star; \psi, j) = \ln w_t(i) + \ln h(i, i^\star; \psi, j). \tag{5.1}$$

Note that $\ln w_t(i)$ is a job $\times$ time fixed effect in our model since it is the same for all workers. Further, $\ln h(\cdot)$ is the sum of the age effect χ_j and the cumulative specific skill accumulation governed by η. We therefore regress log pre-tax income among

job-stayers in the Panel Survey of Income Dynamics (PSID) on $i \times t$ fixed effects, age fixed effects (normalizing $\chi_0 = 0$ without loss of generality), and tenure on the job, controlling for additional observables.[7] The age dummies correspond to the χ_j in the model, while the coefficient on job tenure is equal to η. We estimate $\eta = 0.034$ so that workers skill improve 3.4% per year, in line with the estimates of Kambourov and Manovskii (2009b).

To discipline the distribution of initial skills, observe that workers who switch from sector $i^\star$ to i will experience a wage change of

$$\Delta \ln y_t^{pre}(i, i^\star; \psi, j) = [\ln w_t(i) - \ln w_t(i^\star)] + \psi. \tag{5.2}$$

Note further that one can form an estimate of $\ln w_t(i)$ as the $i \times t$ fixed effects in equation (5.1) estimated on job-stayers alone. Rearranging equation (5.2) implies that one can form an estimate of a worker's relative skills as

$$\psi = \Delta \ln y_t^{pre}(i, i^\star; \psi, j) - \left[\widehat{\ln w_t(i)} - \widehat{\ln w_t(i^\star)}\right] \tag{5.3}$$

where $\widehat{\ln w_t(i)}$ is the estimated wage level in occupation i in period t inferred from the fixed effects as discussed above. Simply put, one can infer relative skills by looking at the change in realized earnings relative to the changes that would be predicted if all workers were paid the same amount in every occupation. Specializing equation (5.3) to those who switch at the beginning of life will therefore yield an estimate of individuals' draw of ψ_0, since early-career workers are both very likely to work in $i^\star$ and have not had time to accumulate specific skills on the job.

We estimate individual level ψ's following equation (5.3) using data from the Current Population Survey (CPS)'s Displaced Worker Supplement (DWS).[8] Focusing on displaced workers generates arguably more exogenous switches between jobs since these workers did not choose to leave their initial job. We restrict the sample to 25-27 year olds to focus on early labor market entrants, and trim the top and bottom 10% of the wage change the reduce in the influence of outliers. We then find that the mean wage loss on such a switch is 35% higher than would be predicted by our estimated $\widehat{\ln w_t(i)}$, with a standard deviation of 24.4%. These

[7] Our full set of observables are sex $\times$ education $\times$ occupation $\times$ industry $\times$ year fixed effects.

[8] The DWS has been used to argue for the presence of industry-specific human capital; see, for instance Neal (1995). We provide more details on all microdatasets used in our analysis in Appendix C.

numbers map directly into μ_{ψ_0} and σ_{ψ_0}, and indicate substantial average human capital benefits to specialization, but with wide dispersion.

Finally, we calibrate the cost of changing one's specialization away from their innate type $\kappa = 4$ to reflect the fact that going to college is around four times average income, which we may normalize to 1. The dispersion of this specialization cost is estimated by Smeets et al. (2026) who study how trade shocks affect major choice in Denmark. We employ their estimate directly.

Internal Calibration. We calibrate several moments internally to match important features of the data. We choose the initial productivities of each sector i, z_i, and the innate talent distribution $G(\theta)$ to match the level of employment and wages in each job i in the initial steady state. We then discipline the $\gamma(i)$ function so that the model matches the level of employment in each i in 2005 after the transition has gone underway. We report these moments in Appendix C (and will report the fit when we have it).

This leaves three parameters to calibrate: the reallocation opportunity arrival rate λ, and the long run elasticities of labor supply within and between sectors: $\underline{\zeta}$ and $\bar{\zeta}$. The frequency of job switches informs the noise parameter $\bar{\zeta}$, and we choose $\underline{\zeta}$ to match a cross-sector labor supply elasticity of 2 following Caliendo et al. (2019). We choose λ to match Artŭc et al. (2010)'s estimate that 95% of reallocation to a one-time permanent trade shock occurs within 8 years. Our computational approach to simulating the model is provided in Appendix B.

The internal calibration is still in progress so we do not yet have numbers to show. All that remains to discuss is the calibration of the voting block.

5.2.2 Calibrating the Voting Block

As discussed above, the shape of the voting function is important for political support for transitions on both the micro and macro level. To make progress on estimating this shape, we combine commuting-zone (CZ) level estimates of earnings losses from trade with commuting zone voting records.

We begin by estimating the predicted earnings losses from trade at the CZ level by estimating the same regression as Autor et al. (2013) – detailed in Appendix C – and multiplying the estimated effect of one additional unit of trade exposure by each CZ's initial trade exposure. This gives the predicted marginal effect of trade

on earnings, and serves as our proxy of $\hat{W} \equiv W_t^{\text{undo}}/W_t^{\text{status quo}}$.[9] We then proxy the probability of voting to rollback trade liberalization with the CZ-level Trump vote share produced by Autor et al. (2020).

One can then estimate the relationship between our proxy for voting to undo the transition (voting for Trump) and our proxy for $\hat{W}$ (predicted earnings losses from trade). We begin by supposing a particular common functional form for $\mathcal{F}\left(\hat{W}\right)$, namely that it takes the logit choice form generated by the random voting model of Persson and Tabellini (2000):

$$\mathcal{F}\left(\hat{W};\nu\right) = \frac{\exp\left(\nu\hat{W} - \alpha\right)}{1 + \exp\left(\nu\hat{W} - \alpha\right)}.$$

The parameter ν governs how sensitive voting to maintain the status quo transition is to losses in economic value.[10] The binary voting function obtains if $\nu \to \infty$, while the voting hazard is flat if $\nu \to 0$. This assumption suggests the following regression to estimate the parameter ν:

$$\ln\left(\frac{1-\mathcal{F}_z}{\mathcal{F}_z}\right) = \alpha - \nu\hat{W}_z + X_z'\beta + \varepsilon_z, \tag{5.4}$$

where $\mathcal{F}_z$ is the share of CZ's population that vote to maintain the status quo – one minus the Trump vote share – and X_z is a set of controls.

Table (5.4) reports the estimates of equation 5.4 in the cross section of commuting zones from 2016. Column 1 weights commuting zones by their share of all votes, while column 2 is unweighted. We control for the Bush share in the 2000 election to account for a CZ's baseline Republican tendencies. The table reveals an estimate of ν between 0.67 and 0.83, depending on weights. We use $\nu = 0.67$ as our baseline parameterization.

[9] Of course, static earnings do not correspond to continuation values, but may be computed substantially more transparently. Out-migration from CZs would also confound this exercise; however, Autor et al. (2025) find limited out-migration of incumbent workers following a trade shock.

[10] This functional form may be microfounded by supposing voters have i.i.d. preferences to vote for the transition drawn from a Type 1 Extreme value distribution with scale parameter $1/\nu$ and mean $-\alpha\nu$.

Table 5.2: Estimates of voting sensitivity

	Weighted (1)	Unweighted (2)
W^{undo}/W_t	0.670^{***}	0.834^{***}
	(0.225)	(0.167)
Log Odds: Bush '00	1.192^{***}	1.170^{***}
	(0.030)	(0.031)
N	722	722
R^2	0.69	0.67

Notes: This table reports estimates of equation (5.4) using US commuting zones. The dependent variable in each regression is the log-odds ratio of the Trump vote share in the 2016 presidential election. W^{undo}/W_t is proxied by the commuting-zone earnings losses from the China shock, predicted following Autor et al. (2013). Column 1 weights commuting zones by their vote shares in 2016, while column 2 reports unweighted estimates. Both regressions control for the log-odds ratio of the Bush vote share in 2000.

How well does the logit functional form fit the data? We present two pieces of evidence that suggest the logit functional form is an appropriate approximation of the data. First, the functional form fits the data well, with an R^2 of 0.67 to 0.69 in this log-odds specification.

Second, Figure 5.2 plots the non-parametric relationship between Trump vote shares and predicted earnings losses from trade. Each dot in the figure corresponds to a commuting zone, with the size of the dot representing the share of all votes that each CZ accounts for. The vertical axis is the log odds ratio of voting for Trump, while the horizontal axis reports the predicted earnings losses from trade. We residualize both axes against the log odds ratio of voting for Bush in 2000. We then fit two non-parametric estimators to the data. The dashed line reports estimates from a locally-weighted sum of squares (LOWESS) estimator, while the red line reports local linear regressions on the data weighted by vote shares. Both lines show an almost perfectly linear relationship between residualized earnings losses and Trump vote shares. This suggests that the logit form, which imposes a linear relationship between this log-odds ratio and earnings losses, is an good approximation of the data. Given the low estimate of $\nu = 0.67$, we find we are quite far from the binary example considered in section 3.3, so that there are strong intensive margin effects on voting.

5.3 Quantitative Exercises

This section is in progress. As mentioned above we plan to carry out three exercises:

1. Present the model-implied path of support for the rolling back of free trade. This exercises serves both as validation of the model by comparing against the polling data of section 4 and as a way to illustrate when it becomes too late to undo the transition (absent further shocks).

2. Study the effect of changing the tax and transfer system on political support. This will have two components. First, we plan to show how changing the level of labor income taxes tilts political support. In this model, a higher labor income tax amplifies the effective comparative advantage of capital in all tasks, as labor's effective cost is higher. This generates a "double whammy" for workers – they are both taxed and offshored at a higher rate. Second, we study whether redistributive policies could have helped alleviate the strength and duration of the backlash phase in the early 20th century.

3. Consider the political implications of a second China shock, which now appears to be affecting relatively high-skill industries. To actualize this, we will unexpectedly change the path of q_t beginning in 2020 so that the long run q_∞ is lower. This simulates an unexpected additional gain in the competitiveness of Chinese imports. We will present a range of scenarios for how large the q_∞ decline is for transparency and to stimulate discussion.

6 Discussion

Our paper studies the political economy implications of sectoral transitions arising from labor market considerations. We unearth a novel wave-shaped pattern of support for maintaining the status quo transition, and show that there may be periods of substantial backlash leading to a political desire to undo the transition. The same economics in principle should apply in other settings in which a new technology gradually becomes cheaper and replaces workers. We have shown that this wave pattern is visible in data for trade, but one could imagine similar dynamics occurring for automation waves, which may have important implications for the political response to artificial intelligence (AI).

However, it is worth emphasizing that our paper's mechanism operates solely through labor markets, while other considerations may matter more in other settings. We discuss these below.

Uncertainty. Our paper has assumed all agents have perfect foresight over the path of q_t. In some settings, such as the rollout of AI, there may be substantial uncertainty about this path. With risk averse agents, there may be additional political will to reverse or slow the decline in q_t if doing so would provide more certainty and ensure less volatile income and consumption.

On the other hand, the political economy we focus on in our paper could generate uncertainty of its own by introducing political risk. Agents may make reallocation decisions assuming that the status quo transition will continue, only for a political shift to cause an undoing of the transition. This prospect would lead workers to reallocate more slowly through wait-and-see effects. However, one would still expect to see a wave-shaped pattern, as this holds even in the economy without skill accumulation in which there are no forward-looking decisions.

Capital Owners. We have focused on the political economy of labor markets in this paper. A broader treatment of the political economy of sectoral transitions would need to consider the political importance of the owners of the alternative factor of production. In our model, the alternative factor k is produced competitively so that owners of this factor earn zero profits and are indifferent between undoing and continuing the transition. If improvements in the productivity of the alternative factor generated profits, the owners of this factor would then matter for the political economy of undoing such a transition.

This is unlikely to be a major consideration in the trade context, since any profits from Chinese firms producing goods-for-export likely accrue to Chinese firm owners who largely do not vote in US elections, and US workers often cannot buy stakes in Chinese companies. One might think such considerations may be more important for automation technologies, whose owners are more involved in domestic politics. However, the distribution of ownership and capital income is extremely skewed, so that only a small share of voters are likely to benefit from the profits generated by the improved productivity of capital. Thus the voting behavior of capital owners is unlikely to change our conclusions per se. For capital own-

ers to matter for aggregate political will, one would likely need to consider models in which capital owners can lobby to influence workers' preferences to undo the transition as in Grossman and Helpman (1996b). Considering such a model in the context of sectoral transitions is fertile ground for future research.

Tax Revenues. In practice, undoing the transition may involve taxing the alternative factor of production by, for instance, imposing tariffs. Such taxes raise revenue for the government, which can in turn be redistributed to households. We abstract from tax revenues of undoing a transition to illustrate the economics underlying the wave pattern as transparently as possible. If undoing the transition carried additional fiscal benefits, support for undoing the transition will generally be higher, and the period over which it is politically feasible to undo the transition will be longer.

7 Conclusion

Sectoral transitions do not only reshape labor markets; they reshape the politics that could reverse them. This paper asked when it becomes politically too late to undo a labor-displacing transition. The answer turns on the slow and irreversible adjustment of workers' skills. Because undoing a transition restores prices but not skills, the constituency for rolling back the transition dissolves as displaced workers reallocate, accumulate expertise elsewhere, and are replaced by cohorts who never specialized in the old economy. Political support therefore moves in a wave — a honeymoon of broad gains, a backlash concentrated among workers trapped in declining sectors, and an eventual acceptance — so that opposition to a transition, however intense, is typically finite-lived. Three decades of American polling on trade show evidence for this wave. Because voting responds to the intensity of losses rather than to a simple head count, the backlash is driven by a deeply affected minority whose political weight peaks and then fades as the economy moves on. The window in which a transition can be undone opens late and, eventually, closes for good.

Our framework suggests several directions for future research. The most immediate is prospective: applied to generative AI, the model implies that the econ-

omy currently sits in the honeymoon phase of a transition whose backlash is yet to come, and it could be used to forecast that backlash's timing and depth. On the theory side, we have characterized how support for undoing a transition evolves while taking the political process as given; endogenizing that process – politicians who time restorationist appeals to the crest of the wave, and the equilibrium consequences of workers anticipating them – is a natural next step. Finally, our measurement of the voting hazard exploited regional variation in trade exposure and voting; individual panel data linking workers' labor-market histories to their political behavior would sharpen estimates of this crucial object across settings.

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Appendix

A Characterizing Equilibrium

We now state and characterize the solution to the workers' and firm's problems.

A.1 Workers

Workers' values. At birth, workers are indexed by their idiosyncratic innate ability $\theta \in [0,1]$ with $\theta \sim G$. During their specialization phase, workers choose an occupation $i^\star$ to specialize in subject to independent amenity shocks following an extreme value type-I distribution. All workers begin with age $j = 0$ and start with $\psi = \psi^{\text{endow}}$ in the occupation they specialize in. Therefore, the probability that a worker born with innate ability θ chooses to specialize in occupation $i^\star$ is

$$p^{\text{train}}(i^\star;\theta) = \frac{\exp\left(W_t(j,\psi,i^\star,i^\star)|_{j=0,\psi=\psi^{\text{endow}}} - \kappa(i,\theta)\right)}{\int \exp\left(W_t(j,\psi,i',i')|_{j=0,\psi=\psi^{\text{endow}}} - \kappa(i',\theta)\right) di'} \tag{A.1}$$

During the subsequent production phase,, workers are indexed by $\mathbf{x} \equiv (j,\psi,i,i^\star)$, which corresponds to their age j, their specific human capital ψ, their current occupation i, and the occupation $i^\star$ that they originally specialized in. In the following, we let $W_t(j,\psi,i,i^\star)$ denote a worker's value. Workers supply labor in their current occupation and earn $h(\varphi,\psi,i,i^\star)\, w_t(i)$, where $w_t(i)$ is the wage per efficiency unit that prevails in their occupation, and $h(\varphi,\psi,i,i^\star)$ is their effective productivity (2.7). Workers receive an opportunity to reallocate to another occupation at rate λ. At that point, they decide which occupation, if any, they want to reallocate to. Recursively,

$$\begin{aligned}\rho W_t(j,\psi,i,i^\star) = {} & h(j,\psi,i,i^\star)\, w_t(i) \\ & + \lambda\left\{\max_{i'} W_t(j,\psi,i',i^\star) - W_t(j,\psi,i,i^\star)\right\} \\ & + \frac{d}{d\epsilon} W_{t+\epsilon}(j+\epsilon,\psi+\eta(i,i^\star)\epsilon,i,i^\star),\end{aligned} \tag{A.2}$$

where the drift in specific skills $\eta(i,i^\star)$ is given by expression (2.9). Totally differ-

entiating the last term

$$\begin{aligned}\rho W_t\left(j,\psi,i,i^\star\right) = & h\left(j,\psi,i,i^\star\right) w_t\left(i\right) \\ & + \lambda\left\{\max_{i'} W_t\left(j,\psi,i',i^\star\right) - W_t\left(j,\psi,i,i^\star\right)\right\} \\ & + \eta\left(i,i^\star\right)\partial_\psi W_t\left(j,\varphi,\psi,i,i^\star\right) + \partial_j W_t\left(j,\varphi,\psi,i,i^\star\right) \\ & + \partial_t W_t\left(j,\varphi,\psi,i,i^\star\right) \end{aligned} \tag{A.3}$$

The boundary condition is

$$W_t\left(J,\psi,i,i^\star\right) = 0 \tag{A.4}$$

when the worker retires at age $j = J$, for any $(\psi, i, i^\star)$.

Distribution and effective labor supplies. We let $\mu_t\left(j,\psi,i,i^\star\right)$ denote the distribution of workers' idiosyncratic states. The evolution of this distribution is determined by the flows described in workers' values. We will state the law of motion in Appendix B.2. Accordingly, the effective labor supplies in each occupation i are

$$l_t\left(i\right) = \int\int\int \exp\left(h\left(j,\psi,i,i^\star\right)\right)\mu_t\left(dj,d\psi,i,di^\star\right) \tag{A.5}$$

A.2 Firms

The two firms can be consolidated into a single entity, which solves

$$\begin{aligned}\max_{\{K_t,\{k_i,l_i\}\}} & F\left(\left\{l_i + \gamma\left(i\right)k_i\right\}\right) - q_t K_t - \int w_{i,t} l_i di \\ \text{s.t.} & \int k_{i,t} = K_t \quad \text{and} \quad k_{i,t} \geq 0 \;\forall i \in [0,1]\end{aligned} \tag{A.6}$$

Note that the specialization choice (2.6) together with the fact that labor reallocation is slow ($\lambda < \infty$) ensure that labor supply is positive in every occupation i at any given point in time. Therefore, occupations are never fully automated. At optimum, the firm chooses its labor demand so the marginal product of labor in each occupation equals the wage there

$$F_i\left(\left\{l_{i',t} + \gamma\left(i'\right)k_{i',t}\right\}_{i'}\right) = w_{i,t} \tag{A.7}$$

In turn, there exists a Lagrange multiplier $\varsigma_t > 0$ on the constraint $\int k_{i,t} = K_t$ such that the demand for automation satisfies

$$\gamma(i) F_i\left(\left\{l_{i',t} + \gamma\left(i'\right) k_{i',t}\right\}\right) \begin{cases} = \varsigma_t & \text{if } k_{i,t} > 0 \\ < \varsigma_t & \text{if } k_{i,t} = 0 \end{cases} \tag{A.8}$$

It is worth noting that the degree of automation is each occupations is not necessarily ranked by their index i. The reason is that the labor supplies $l_{i,t}$ are not necessarily monotonic as a function of i, depending on the distribution of innate abilities $G(\theta)$, workers' reallocation over time, etc. At optimum, the Lagrange multiplier ς_t ensures that the firm uses all its automation

$$\sum_i k_{i,t} = K_t \tag{A.9}$$

at any given point in time. In turn, the optimal choice of K_t pins down the Lagrange multiplier

$$\varsigma_t = q_t \tag{A.10}$$

B Computational Appendix

We now explain how we solve the model numerically.

B.1 Solving for Workers's Values

We now explain how we discretize and solve for workers' values.

Grids. We discretize time so $t \in \{0, \Delta, 2\Delta, \ldots\}$ for some $\Delta > 0$. We proceed similarly to discretize workers' ages j. We let $\Delta \equiv 1/4$ so each period corresponds to a quarter. We also discretize the occupations i over $I \in \mathbb{N}$ points between 0 and 1. Finally, we discretize specific human capital so $\psi \in \left\{0, \hat{\Delta}, 2\hat{\Delta}, \ldots, \hat{\psi}\right\}$ with $\hat{\Delta} > 0$, where $\hat{\psi}$ is the upper bound on that grid.

Finite difference scheme. Our finite difference scheme is implicit over occupations i. That is, we evaluate the continuation values associated with changes in i in period

t. In particular, the reallocation decision is computed using continuation values evaluated in period $t + \Delta$ to obtain a linear system in current values. In turn, our scheme is also implicit in specific human capital ψ when it resets to $\psi = 0$ as workers move between occupations. In contrast, our scheme is explicit in specific human capital ψ when it comes to its accumulation on the job, which allows us to parallelize our numerical solution over ψ to speed up the computations. In this case, we evaluate the continuation values associated with changes in ψ in period $t + \Delta$. As usual, the scheme is explicit in age j and time t, so we evaluate the continuation values associated to aging or the passing of time in period $t + \Delta$. Workers' values can be solved separately for each value of the occupation $i^\star$ that workers specialized in.After discretization, workers' values (A.3) become

$$\begin{aligned}\rho W_t\left(j,\psi,i,i^\star\right) = {} & h\left(\psi,j,i,i^\star\right) w_t\left(i\right) \\ & + \lambda \sum_{i'} p_{t+\Delta}\left(i';j,\psi,i,i^\star\right) \times \\ & \qquad \left[W_t\left(j,\psi,i',i^\star\right) - W_t\left(j,\psi,i,i^\star\right)\right] \\ & + \eta\left(i,i^\star\right) \frac{W_{t+\Delta}\left(j+\Delta,\psi+\hat{\Delta}\left(i,i^\star\right),i,i^\star\right) - W_{t+\Delta}\left(j+\Delta,\psi,i,i^\star\right)}{\hat{\Delta}\left(i,i^\star\right)} \\ & + \frac{W_{t+\Delta}\left(j+\Delta,\psi,i,i^\star\right) - W_t\left(j,\psi,i,i^\star\right)}{\Delta},\end{aligned} \tag{B.1}$$

where $\hat{\Delta}\left(i,i^\star\right) \equiv \hat{\Delta} > 0$ if $i = i^\star$ and $\hat{\Delta}\left(i,i^\star\right) = -\hat{\Delta} < 0$ otherwise.

Numerical solution. It is useful to define the following square transition matrices

$$\mathbf{M}_{t+\Delta}\left(j+\Delta,\psi,i^\star\right) = \mathbf{M}^{\text{out}}_{t+\Delta}\left(j+\Delta,\psi,i^\star\right) + \mathbf{M}^{\text{in}}_{t+\Delta}\left(j+\Delta,\psi,i^\star\right) \tag{B.2}$$

with the diagonal matrices

$$\mathbf{M}^{\text{out}}_{t+\Delta}\left(j+\Delta,\psi,i^\star\right)_{[i,i']} = -\mathbf{1}_{\{i'=i\}} \lambda \sum_{\hat{i}} p_{t+\Delta}\left(\hat{i};j+\Delta,\psi,i,i^\star\right) \tag{B.3}$$

and the square matrices

$$\mathbf{M}^{\text{in}}_{t+\Delta}\left(j+\Delta,\psi,i^\star\right)_{[i,i']} = \lambda p_{t+\Delta}\left(i';j+\Delta,\psi,i,i^\star\right), \tag{B.4}$$

for any state (j, ψ, i, i'). We also define the square discounting matrix

$$\mathbf{\Lambda} = \left(\rho + \frac{1}{\Delta}\right) \mathbb{I}, \tag{B.5}$$

where $\mathbb{I}$ is the identity matrix whose size corresponds to the number of occupations i.

Algorithm 1. Solve the system (B.1).

Step 0. Let the terminal values $W_T(J, \psi, i, i^\star) = 0$ for all $(\psi, i, i^\star)$ when the worker retires at age J. Initiate the recursion by setting the time index to $t = T - \Delta$ and the age index to $j = J - \Delta$.

Step 1. Compute the reallocation probabilities $p_t(i'; j, \psi, i, i^\star)$ using (2.10). Compute the transition matrices $\mathbf{M}_{t+\Delta}(j + \Delta, \psi, i^\star)$ using (B.2)–(B.4).

Step 2. Solve for workers' values:

Solve for the values

$$\mathbf{W}_t(j, \psi, i^\star) = \left[\mathbf{\Lambda} - \mathbf{M}_{t+\Delta}(j + \Delta, \psi, i^\star)\right]^{-1} \mathbf{B}_t(j, \psi, i^\star), \tag{B.6}$$

where the vectors

$$\mathbf{W}_t(j, \psi, i^\star)_{[i,1]} \equiv W_t(j, \psi, i, i^\star), \tag{B.7}$$

contains workers' values, and the vectors

$$\begin{aligned}\mathbf{B}_t(j, \psi, i^\star)_{[i,1]} \equiv\ & h(j, \psi, i, i^\star)\, w_t(i) \\ & + \eta(i, i^\star) \frac{W_{t+\Delta}\left(j + \Delta, \psi + \hat{\Delta}(i, i^\star), i, i^\star\right) - W_{t+\Delta}(j + \Delta, \psi, i, i^\star)}{\hat{\Delta}(i, i^\star)} \\ & + \frac{W_{t+\Delta}(j + \Delta, 0, i, i^\star)}{\Delta}\end{aligned} \tag{B.8}$$

capture workers' flow earnings, changes in specific human capital ψ which are part of our explicit scheme, and the evolution of time t and age j.

Step 3. Set the age $j' = j - \Delta$, repeat Steps 1–2, and continue until $j = 0$.

Step 4. When solving for transitions, set $t' = t - \Delta$, repeat Steps 1–3 in that period, and continue until $t = 0$. This last step is redundant when solving for the initial and final steady states.

B.2 Effective Labor Supplies

We now explain how to iterate on the distribution of workers' idiosyncratic states $\mu_t(j, \psi, i, i^\star)$. As usual, the law of motion for the effective labor supplies is closely related to the recursive formulation of workers' values (Appendix B.1). In particular, the transition matrices $\mathbf{M}_t(j, \psi, i^\star)$ capture all the relevant flows, except for changes in specific human capital ψ which are part of our explicit scheme.

Let

$$\boldsymbol{\mu}_t(j, \psi, i^\star)_{[i,1]} \equiv \mu_t(j, \psi, i, i^\star), \tag{B.9}$$

Then, the distribution evolves as

$$\begin{aligned}\boldsymbol{\mu}_{t+\Delta}(j+\Delta, \psi, i^\star) = &\left[\mathbb{I} + \mathbf{M}_t(j, \psi, i^\star)' \Delta\right] \boldsymbol{\mu}_t(j, \psi, i^\star) \\ &+ \eta(i, i^\star) \Delta / \hat{\Delta}(i, i^\star) \left[\boldsymbol{\mu}_t\left(j, \psi - \hat{\Delta}(i, i^\star), i^\star\right) - \boldsymbol{\mu}_t(j, \psi, i^\star)\right]\end{aligned} \tag{B.10}$$

for any $j = 0, \Delta, 2\Delta, \ldots, J - \Delta$ and any $i^\star$. The expression above assumes that workers transition across grid points for ψ according to a non-stochastic simulation (Young, 2010): a deterministic share of workers transitions from one point to the next based on how large the drift $\eta(i, i^\star)\Delta$ is relative to the step $\hat{\Delta}(i, i^\star)$.[11] The terms $\eta(i, i^\star)$ and $\hat{\Delta}(i, i^\star)$ were defined in expressions (2.9) and (B.1), respectively.

Newborn workers with $j = 0$ are endowed with a reference skill $\psi = \psi^{\text{endow}}$ and an innate ability $\theta \sim G$. They choose an occupation $i^\star$ to specialize in with probability

$$p^{\text{train}}(i^\star; \theta) = \frac{\exp\left(W_t(j, \psi, i^\star, i^\star)|_{j=0, \psi=\psi^{\text{endow}}} - \kappa(i, \theta)\right)}{\int \exp\left(W_t(j, \psi, i', i')|_{j=0, \varphi=0, \psi=\psi^{\text{endow}}} - \kappa(i', \theta)\right) di'} \tag{B.11}$$

Accordingly, the distribution of workers' states among newborn workers is

$$\mu_t(j, \psi, i, i^\star)|_{j=0} = \begin{cases} \frac{\Delta}{J} \int \int p^{\text{train}}(i^\star; \theta) \, d\Psi(\psi) \, G(d\theta) & \text{if } i^\star = i \\ 0 & \text{otherwise} \end{cases}, \tag{B.12}$$

where Δ / J is the mass of newborns in a given period.

[11] We choose our grids so $|\eta(i, i^\star)| \Delta < \hat{\Delta}$.

The effective labor supplies (A.5) in each occupation i are given by

$$l_t(i) = \sum_j \sum_\psi \sum_{i^\star} \exp\left(h\left(j,\psi,i,i^\star\right)\right) \mu_t\left(j,\psi,i,i^\star\right) \tag{B.13}$$

B.3 Solving for Firm's Automation Choice

The optimal automation choice is fully characterized by expressions (A.7)–(A.10). As in Appendix B.1, we discretize the occupations so i over $I \in \mathbb{N}$ points between 0 and 1. The production function admits a constant elasticity of substitution ϕ so

$$F\left(\{l_{i,t} + \gamma(i)\, k_{i,t}\}\right) = \left[\sum_i \vartheta^{\frac{1}{\phi}} \left(l_{i,t} + \gamma(i)\, k_{i,t}\right)^{\frac{\phi-1}{\phi}}\right]^{\frac{\phi}{\phi-1}} \tag{B.14}$$

where the coefficient $\vartheta \equiv 1/I$ is the weight associated with each occupation. Note that

$$\begin{aligned} F_i\left(\{l_{i',t} + \gamma(i)\, k_{i',t}\}\right) &= \vartheta^{\frac{1}{\phi}} \left(l_{i,t} + \gamma(i)\, k_{i,t}\right)^{-\frac{1}{\phi}} \left[\sum_{i'} \vartheta^{\frac{1}{\phi}} \left(l_{i',t} + \gamma\left(i'\right) k_{i',t}\right)^{\frac{\phi-1}{\phi}}\right]^{\frac{1}{\phi-1}} \\ &= \left[\vartheta \left(1 + \frac{\sum_{i' \neq i} \left(l_{i',t} + \gamma\left(i'\right) k_{i',t}\right)^{\frac{\phi-1}{\phi}}}{\left(l_{i,t} + \gamma(i)\, k_{i,t}\right)^{\frac{\phi-1}{\phi}}}\right)\right]^{\frac{1}{\phi-1}} \end{aligned} \tag{B.15}$$

Solving for the firm's optimal choices is thus straightforward. First, the investment cost q_t pins down the Lagrange multiplier λ_t in expression (A.10). Fixing labor supplies $\{l_{i,t}\}$ in all occupations and automations $\{k_{i',t}\}$ in other occupations, the demands for automation (A.8) can be easily inverted to obtain an unconstrained demands $k^\star_{i,t} \in \mathbb{R}$. The actual automation level in a given occupation $k_{i,t}$ is either $k^\star_{i,t}$ when this quantity is positive or zero otherwise. Therefore, using expression (B.15),

$$k_{i,t} = \max\left\{\frac{1}{\gamma(i)}\left[\left(\frac{\sum_{i' \neq i} \left(l_{i',t} + \gamma\left(i'\right) k_{i',t}\right)^{\frac{\phi-1}{\phi}}}{\vartheta^{-1}\left(\frac{q_t}{\gamma(i)}\right)^{\phi-1} - 1}\right)^{\frac{\phi}{\phi-1}} - l_{i,t}\right], 0\right\} \tag{B.16}$$

for each occupation i. This fixed point problem in $\{k_{i,t}\}$ can be solved iteratively, starting with an initial guess $k_{i,t} = 0$ in each occupation, updating this guess using expression (B.16), and repeating until convergence. In turn, the labor demands (A.7) combined with the labor market conditions in each occupation yield the equilibrium wages

$$w_{i,t} = \left[\vartheta \left(1 + \frac{\sum_{i' \neq i} \left(l_{i',t} + \gamma\left(i'\right) k_{i',t} \right)^{\frac{\phi-1}{\phi}}}{\left(l_{i,t} + \gamma\left(i\right) k_{i,t} \right)^{\frac{\phi-1}{\phi}}} \right) \right]^{\frac{1}{\phi-1}} \tag{B.17}$$

for each occupation i. Finally, the constraint (A.9) pins down the aggregate level of automation.

C Details on Quantitative Application

C.1 Data Sources and Cleaning

Current Population Survey (CPS). We use an IPUMS-CPS extract covering the basic monthly samples and the March Annual Social and Economic Supplement (ASEC) from 1980 through 2025. We restrict attention to respondents aged 25–65 and drop those living in group quarters. Earnings variables – hourly wages and weekly earnings of outgoing-rotation respondents, and annual wage and total income in the ASEC – are cleaned of not-in-universe and topcode flags, deflated by the monthly CPI-U, and the bottom 1% of each real earnings distribution is winsorized within year. Exploiting the CPS's 4-8-4 rotation design, we reconstruct each respondent's month in sample from the IPUMS person identifiers, which allows us to link the two outgoing-rotation interviews that occur twelve months apart. These linked earnings pairs underlie the CPS wage-growth and industry-switching moments. Industry is measured throughout on the time-consistent census IND1990 classification (243 industry cells), onto which we merge the trade-exposure rankings of Appendix C.2.

CPS Displaced Worker Supplement (DWS). The DWS has been fielded as a supplement to the CPS roughly biennially since 1984. It identifies workers who lost a job in the preceding years because their plant closed, their position was abolished, or work was slack, and records weekly earnings on the lost job along-

side current earnings. We measure displacement losses using weekly earnings rather than hourly wages, both because weekly earnings capture the decline in hours that accompanies displacement and because hourly wages on the lost job are recorded only from 2002 onward, leaving samples too small for our purposes. We drop observations carrying the IPUMS non-response and not-in-universe codes on the earnings variables, but retain topcoded earners. The sample used to calibrate ψ_0 consists of workers displaced at ages 25–27 who report no job between the displacement and the survey, so that the earnings comparison spans a single employer-to-employer transition; we describe the resulting moments in Appendix C.3.

Panel Study of Income Dynamics (PSID). We use the 1968–1980 waves of the PSID, restricted to household heads aged 25–65 with positive annual hours and labor income. The wage is measured as head labor income divided by annual hours, and we remove the few topcoded observations with a 1/99 percent trim within year. Crucially, we attach the PSID's retrospective occupation-industry files, which recode every head's industry on a consistent three-digit 1970-census basis and correct the well-documented measurement error in the original year-by-year codes; these cleaned codes are available only through 1980, which conveniently corresponds to our pre-transition initial steady state. Industry tenure is accumulated within these consistently-coded spells. The estimation sample contains roughly 38,000 head-year observations; all regressions use PSID individual weights and cluster standard errors by person.

Commuting-zone trade exposure and voting data. The voting calibration uses two publicly available replication datasets. From Autor et al. (2013) we take the commuting-zone (CZ) panel of 722 CZs observed over two stacked periods (1990–2000 and 2000–2007, the latter rescaled to a decadal equivalent), including the change in Chinese import exposure per worker, its instrument, and the full set of CZ controls. From Autor et al. (2020) we take county-level Republican two-party vote shares in the 2000 and 2016 presidential elections, which we collapse to CZs weighting counties by total votes cast. The two datasets merge one-to-one on commuting zone, with all 722 CZs matching.

Quarterly Census of Employment and Wages (QCEW). The employment and wage targets for the internal calibration come from the BLS QCEW annual files at the national level, summed across ownership codes. The QCEW reports sectoral em-

ployment and weekly wage information quarterly back to 1975. Because QCEW industry detail is on the SIC classification before 1990, our 1980 targets require harmonization. We map four-digit SIC employment to NAICS using the Census SIC1987-to-NAICS1997 concordance, splitting each SIC cell across its NAICS targets in proportion to NAICS employment in 1990, the closest year observed on both classifications. The harmonized 1980 file recovers 99.7% of the BLS-published 1980 national employment control total.

Gallup World Affairs poll. The opinion series in Figure 4.1 is built from Gallup's published World Affairs poll tabulations, which have asked "Do you see foreign trade more as an opportunity for economic growth through US exports or a threat to the economy from foreign imports?" periodically since the early 1990s with a consistent sampling frame. We plot the share of respondents choosing "opportunity;" the complementary series – the share not calling trade a threat – behaves nearly identically.

C.2 Defining and Ranking Trade Exposure

This appendix details the construction of the import-penetration (IP) panel behind the trade-exposure ranking and shows that the ranking is robust to the classification scheme. For each industry i and year t we define $IP_{it} = M_{it} / (M_{it} + Y_{it})$, where M_{it} is imports and Y_{it} is domestic gross output. Goods imports (manufacturing, agriculture, and mining) come from the USITC DataWeb at the six-digit NAICS level for 1997–2016; services trade comes from the BEA International Services tables, allocated to industries via a concordance between BEA service lines and input-output industries, splitting flows across industries in proportion to gross output where a service line maps to several industries. Domestic output Y_{it} is BEA Gross Output by Industry at the detail level of roughly 400 input-output industries, which is available for *every* sector of the economy – not only manufacturing – and whose coverage sets the 1997–2016 sample window. The resulting all-industry IP panel is then mapped to the 243 census IND1990 industry cells used in the CPS. When one input-output industry spans several IND1990 cells, each cell inherits the parent industry's IP series and such siblings share a rank. The handful of IND1990 cells with no input-output counterpart (active-duty military and an unspecified-metals residual), like all cells with no recorded imports, are assigned $IP = 0$. Figure C.1 shows that the cross-industry distribution of import penetration

shifts steadily rightward over the sample, as the model predicts when the foreign frontier q_t falls.

Our baseline classification ranks IND1990 cells by the highest IP ratio attained in-sample. We consider two families of alternatives. The first ranks cells by their IP ratio in the final sample year (2016). The second ranks cells by the time at which their IP series crosses a threshold X, using a four-tier rule: industries already above X at the start of the sample are ranked first (by initial IP); industries that cross X in-sample are ranked next (by crossing year); industries that never cross but whose IP trends upward are ranked by the crossing year projected from a linear fit; and industries with no upward trend are ranked last (by trend slope). We implement this rule for thresholds $X \in \{0.25, 0.50, 0.75\}$ and, as an alternative projection method, replace the linear projection with an exponential (log-linear) projection at $X = 0.50$. Table C.1 reports Spearman rank correlations across all six schemes over the full universe of 243 IND1990 cells. The level-based and linear threshold-crossing rankings are nearly interchangeable, with rank correlations between 0.92 and 1.00; the choice of threshold X is essentially irrelevant (correlation 0.97 and above across thresholds). The exponential projection is the most distinct scheme, with correlations of 0.74–0.82, driven almost entirely by reshuffling among never-crossing low-exposure industries whose projected crossing dates are poorly identified; the most-exposed industries – apparel, footwear and leather, toys, audio-video equipment, and electronic computer manufacturing – sit at the top of every ranking.

Table C.1: Rank correlations across trade-exposure classification schemes

	(1)	(2)	(3)	(4)	(5)	(6)
(1) Highest in-sample IP (baseline)	1.000					
(2) IP in final sample year	0.997	1.000				
(3) Crossing time, $X = 0.25$	0.950	0.958	1.000			
(4) Crossing time, $X = 0.50$	0.923	0.935	0.974	1.000		
(5) Crossing time, $X = 0.75$	0.919	0.932	0.972	0.999	1.000	
(6) Crossing time, $X = 0.50$, exp. projection	0.736	0.754	0.791	0.816	0.817	1.000

Notes: Spearman rank correlations across trade-exposure ranking schemes, computed over all 243 IND1990 industry cells, 1997–2016 IP panel. Threshold-crossing schemes rank industries by the four-tier rule described in the text; "exp. projection" projects never-crossing industries' crossing dates from a log-linear rather than linear trend.

C.3 Externally Calibrated Parameters: η, χ_j, and ψ_0

Estimating η and χ_j in the PSID. As described in the main text, we estimate the regression implied by equation (5.1) on the PSID sample of Appendix C.1: log wages on industry×year fixed effects (the skill prices), single-year age fixed effects (the χ_j profile, normalized to zero at age 25), and years of industry tenure, whose coefficient identifies the specific-skill drift η. Our preferred specification saturates the skill-price controls with the full sex×occupation×industry×year×education interaction and instruments tenure with its deviation from the within-spell mean, following Altonji and Shakotko (1987), to purge the upward bias from match-quality selection – good worker-industry matches both pay more and survive longer, so OLS overstates the return to tenure. Table C.2 reports the tenure coefficient across specifications. The instrumented estimates cluster tightly at $\eta \in [0.029, 0.039]$ regardless of how the skill prices are controlled, while uninstrumented OLS estimates are roughly twice as large, reflecting the positive selection of high-tenure workers. Our baseline $\eta = 0.034$ comes from the maximal-control instrumented specification and sits within the range of Kambourov and Manovskii (2009b). The age fixed effects from the same regression give the general-skill profile χ_j: it rises steeply from 0 at age 25 to 0.14 by 35 and peaks at 0.22 around age 45, plateaus near 0.19–0.20 through the late 50s, and declines to 0.10 by 65 – a standard concave life-cycle profile, here cleaned of the industry-tenure component that a raw age profile would conflate with η.

Table C.2: Return to industry tenure in the PSID, across specifications

Specification	β_τ	s.e.	η	N
OLS, industry×year FE	0.0382	(0.0022)	0.076	38,427
IV, industry×year FE	0.0194	(0.0022)	0.039	38,427
IV, occupation×industry×year FE	0.0187	(0.0023)	0.037	37,959
OLS, person FE	0.0186	(0.0024)	0.037	37,824
IV, person FE	0.0147	(0.0023)	0.029	37,823
IV, sex×occ.×ind.×year×educ. FE (baseline)	0.0168	(0.0024)	0.034	36,448

Notes: Each row reports the coefficient on years of industry tenure from a log-wage regression on PSID heads, 1968–1980, ages 25–65, with single-year age fixed effects and the indicated skill-price controls. "IV" instruments tenure with its deviation from the within-spell mean (Altonji-Shakotko). Standard errors clustered by person; IV standard errors with absorbed fixed effects omit the absorbed-degrees-of-freedom correction and are slightly understated.

Estimating the moments of ψ_0 in the DWS. Following equation (5.3), an individual worker's ψ is the change in log weekly earnings across the displacement, net of the change predicted by the industry×year skill prices $\widehat{\ln w_t}(i)$ estimated on stayers. We compute this object for DWS workers displaced at ages 25–27 with no intervening job (Appendix C.1), for whom accumulated industry tenure is small so that the inferred ψ approximates the entry draw ψ_0, and clip the top and bottom 10% of the distribution. Because ψ_0 in the model is the *specialist's* skill advantage in their chosen sector – a one-sided object – we target the positive branch of the inferred distribution: conditioning on displaced switchers who experience an earnings loss relative to the skill-price prediction yields $\mu_{\psi_0} = 0.350$ and $\sigma_{\psi_0} = 0.244$.

C.4 Internally Calibrated Moments and Model Fit

The internal calibration chooses the sector productivities z_i and the talent distribution $G(\theta)$ to match employment and average wages by sector in the 1980 initial steady state, and the level of the $\gamma(i)$ schedule to match employment by sector after the transition. The empirical targets are constructed from the QCEW as follows. We attach to each detailed input-output industry its percentile in the trade-exposure ranking of Appendix C.2 and group industries into sixteen gridpoints of the exposure percentile. For each gridpoint we compute the employment share and the employment-weighted average real weekly wage (deflated with the CPI-U-RS) in the initial steady state (1980) and in the post-transition steady state, which we measure as the average of 2024 and 2025 to smooth year-to-year noise. One feature of the targets is worth noting: because all non-tradable industries tie at $IP = 0$, the least-exposed gridpoint is large, holding roughly half of employment in 1980 and growing to about 58% post-transition.

The model fit to these targeted moments is in progress.

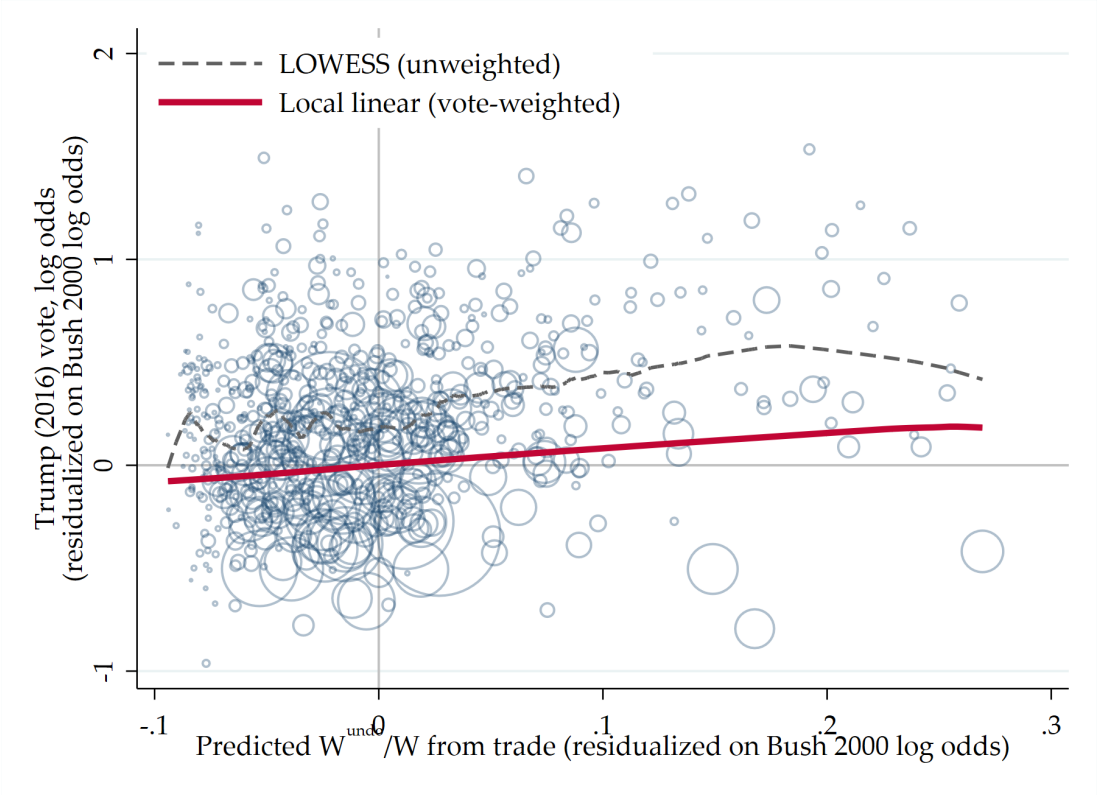
C.5 The Voting Block: Predicted Earnings Losses and Voting Sensitivity

Predicted earnings losses from trade. We re-estimate the commuting-zone earnings regression of Autor et al. (2013) on their replication data. We estimate stacked first differences over 1990–2000 and 2000–2007 for 722 commuting zones, where the outcome is the percent change in average household wage and salary income

per adult and the regressor is the change in Chinese import exposure per worker, in thousands of dollars. Exposure is instrumented with the growth of Chinese imports in eight other high-income economies, weighted by the CZ's lagged industry employment structure; the regression includes the full set of Autor et al. (2013) controls (start-of-period manufacturing employment share, college share, foreign-born share, female employment share, routine-occupation share, offshorability, census-division dummies, and a period dummy), weights periods by start-of-period population, and clusters by state. The two-stage-least-squares coefficient is -2.14 percent per thousand dollars of exposure per worker, with a first-stage F statistic of 47.6, replicating the published estimates. The predicted earnings loss for each CZ is then the *marginal effect of trade* – the coefficient multiplied by the CZ's observed exposure change, summed over the two periods – and *not* the fitted value of the regression, so the controls play no role in the predicted loss. The vote-weighted mean cumulative predicted loss across CZs is 8.0% of household wage income. Our proxy for W^{undo}/W_t in a CZ is one plus its predicted loss expressed as a share.

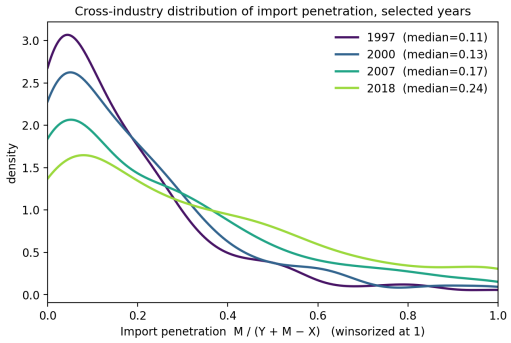
The log-odds regression and the non-parametric figure. We merge the predicted losses onto the CZ-level two-party vote shares for Bush in 2000 and Trump in 2016 constructed in Appendix C.1. Estimating equation (5.4) amounts to regressing the log odds of the CZ's Trump vote share on W^{undo}/W_t and the log odds of its Bush 2000 vote share, which absorbs the CZ's baseline Republican tendency. The estimates in Table 5.2 use all 722 commuting zones with no trimming; column 1 weights CZs by total votes cast in 2000 and column 2 is unweighted. Figure 5.2 is the graphical counterpart of the weighted regression: both the Trump log odds and W^{undo}/W_t are residualized against the Bush 2000 log odds by vote-weighted regressions, and the residuals are plotted against each other with markers proportional to votes cast. The dashed line is an unweighted LOWESS smoother and the solid line a vote-weighted local linear regression, each with bandwidth equal to twice the standard deviation of the horizontal-axis variable. For readability the figure clips the horizontal axis at its 1st and 99th percentiles, which removes a handful of very small, hyper-exposed CZs whose linear extrapolation implies implausibly large losses; the regression estimates in Table 5.2 use the untrimmed sample.

Figure 5.2: Non-parametric relationship between Trump vote shares and predicted earnings losses from trade



Notes: Figure reports the non-parametric relationship between $W^{\text{undo}}/W^{\text{status quo}}$ and the log-odds ratio of the Trump vote share. Both horizontal and vertical axes have been residualized against the log-odds ratio of the 2000 Bush vote share in a regression weighted by commuting zone size. Each dot corresponds to a commuting zone, with the size of the dot proportional to that commuting zone's 2016 vote share. The dashed gray line estimates a Locally Weighted Scatterplot Smoothing (LOWESS) based on the unweighted commuting zone data. The red line reports a local linear regression weighting by vote shares.

Figure C.1: Distribution of NAICS-6 Import Penetration over Time



Notes: Each line plots the kernel density of import-penetration ratios across six-digit NAICS manufacturing industries in the indicated year, winsorized at one. The median rises from 0.11 in 1997 to 0.13 in 2000, 0.17 in 2007, and 0.24 in 2018.