Family and demographic effects in worker response to trade shocks: Results from the matched CPS.*

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Abstract

Rising import competition has repeatedly been shown to depress wages and disrupt local labor markets. This paper asks whether those effects vary systematically across U.S. demographic groups in the context of the 'China Shock'. Using the matched CPS, which follows workers year to year, we study how shocks alter income, hours, and mobility. We find that manufacturing, less-educated, and liquidity-constrained workers are especially vulnerable: poor households are more likely to experience income losses, more likely to exit industries, and less able to increase hours. By contrast, married, educated, and affluent workers are relatively cushioned—less likely to see income losses and less likely to make disruptive switches across industries or occupations. We argue that these patterns reflect liquidity constraints rather than switching costs alone, highlighting a mechanism largely absent from the trade-adjustment literature.

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Numerous researchers have documented income losses in local labor markets hit by rising import competition. In many settings, labor incomes in locations dependent on import-competing industries fall relative to incomes elsewhere.

This paper examines whether these effects differ across demographic groups in the U.S. case, in the context of the most studied example, commonly referred to as the 'China Shock.' We use the 'matched CPS,' which allows us to observe year-to-year economic transitions of a sample of U.S. workers, to see if the losses in labor income and related adjustments fall more heavily on identifiable demographic groups. This is of potential policy importance because it can help identify who gains and who loses from trade opening, and thus inform policy to help those who lose and spread the gains from trade. Our guess was that for workers whose switching or moving costs are higher (such as might be the case for married workers or workers who are parents), their income losses from a given shock are likely to be greater than those for workers who can switch industry, occupation, or location more easily.

This initial hypothesis is, however, not completely consistent with the data. We find that income losses are more likely in the face of a trade shock among manufacturing, younger, and poor workers, while married and bachelor's-degree workers are relatively protected. Poor households, in particular, are more likely to experience income and hours losses and more likely to exit industries, suggesting adjustment through necessity rather than protection. Affluent households, by contrast, are more likely to experience income gains and are less likely to undertake disruptive switches across industries or occupations. We interpret these family-income findings as evidence of liquidity constraints: low-income workers scramble to preserve earnings in the face of required expenses, while high-income workers can afford to remain more stable. These effects appear to be new to the trade literature.

To interpret these results, first consider the standard neoclassical model of dynamic labor adjustment as in Artuç, Chaudhuri and McLaren (2010), Dix-Carneiro (2014), or Caliendo, Dvorkin, and Parro (2019) (see McLaren (2017, 2022) for surveys of the literature). In such models, a worker must choose in each period whether to stay in her current industry, occupation, or location, or incur a cost to switch to another. The cost varies over time for each worker, and in many specifications will vary from one worker to another. If the worker's industry is hit with an import-competition shock that lowers the marginal value product of labor and thus wages in the industry, then the worker may move out of the industry or stay, depending on her current switching costs, but the probability of switching will be increased by the trade shock. Workers with higher switching costs will be less likely to switch, and therefore more likely to suffer a loss of income, compared to workers with lower switching costs.

One might call this the 'neo-classical adjustment paradigm.' Based on this class of models, one would expect that demographic groups with higher switching costs would be more likely to see a decline in income when hit with a trade shock[1]. Married workers could be one example. If switching jobs requires a big change in schedule, longer commutes, a night shift, and so on, it could affect a married couple's life together, imposing a cost that would not be present if the worker were single. Workers who have children could be another example. Children impose additional constraints on a worker's time, and the necessity of being available in case of emergency can make it more costly to accept a job with more inflexible hours or a longer commute. Older workers may have trouble switching industry or occupation if it requires learning new skills (Dix-Carneiro (2014) finds strong evidence of this in the case of Brazil). For minority workers, labor discrimination may make it more difficult to move to a new industry as well.

Each of these demographic groups could face higher-than-average costs of switching and therefore be more likely to suffer an income loss in the presence of a trade shock. This is partly consistent with the data: we find that manufacturing, younger, and poor workers are more likely to incur income losses, while married and bachelor's-degree workers are relatively protected. Poor households, in particular, not only face greater income and hours losses but also show a higher likelihood of exiting industries, suggesting that mobility occurs alongside harm rather than offsetting it. Affluent households, by contrast, experience income gains and are less likely to switch, indicating stability rather than disruption. These findings are not easily reconciled with the neoclassical adjustment paradigm alone.

These findings can, however, be rationalized by considering liquidity constraints, an issue absent from the standard neo-classical adjustment model. If a worker has essential expenses that must be met each period, such as mortgage, rent, or debt service, utility payments and basic groceries, and no financial reserves or access to consumer loans, she may need to take extraordinary measures to keep the household income from falling below the level required for those payments in any given period. We show how this can occur in a simple, stylized model of labor supply and intertemporal consumption in the presence of a labor-market shock.

[1] See Artuç, Chaudhuri, and McLaren (2008, 2014) for dynamic labor adjustment models with forward-looking behavior and mobility frictions; Cameron, Chaudhuri, and McLaren (2007) for switching under uncertainty; Caliendo et al. (forthcoming) for a general equilibrium extension; and Artuç, Brambilla, and Porto (2017) for an application to economies with capital immobility.

1 Related literature.

We draw on the rich literature examining the local-labor-market effects of the 'China Shock', starting with Autor, Dorn, and Hanson (2013). That study used increases in imports from China to the US as a measure of the shock, averaged with local employment weights and normalized by local initial labor supply to create a geographically-varying trade shock measure and instrumented by China's exports to third countries. We use the latter formulation by Pierce and Schott (2016), described below, which measures the shock using the change in policy uncertainty that triggered the rising imports, rather than imports themselves.

Most work on this topic has used repeated cross sections, but a small subset has used data that follows individual workers over time. Autor, Dorn, Hanson, and Song (2014) use Social Security administrative data to trace the effects on individual workers over several years. Ebenstein et al. (2014) and Liu and Trefler (2019) are among the few studies to use matched CPS data to follow U.S. workers over time in response to trade shocks. Artuç, Bastos, and Lee (2021) use matched worker-firm data to quantify labor transitions and welfare effects across countries. Devlin, Kovak, and Morrow (2022) do something similar with Canadian administrative data. Pierce, Schott, and Tello-Trillo (2024) pioneer the use of U.S. employee-employer LEHD data to follow workers. Like these studies, we follow individual workers, though our panel structure captures only a single year of transition.

A flurry of recent work has examined differences in adjustment across demographic groups or worker types. Carballo and Mansfield (2022) simulate how workers of different types respond to trade shocks using LEHD and trade exposure data, highlighting heterogeneity in non-employment risk and industry switching[2]. Keller and Utar (2022) study differences in adjustment to a trade shock for men and women in Denmark, finding that, unlike men, a substantial fraction of women respond to an import-competition shock by withdrawing temporarily from the labor force for marriage or childbirth. Brussevich (2018) shows that gender gaps in wage losses from trade liberalization may be explained by differences in sectoral mobility. Hottman and Monarch (2024) study the effects of the 'China Shock' on consumer prices for different US demographic groups, finding that Black workers benefited proportionally less from lower consumer prices than other groups. Kahn, Oldenski, and Park (2023) show that the 'China Shock' modestly reduced Black-White wage differentials in the US, but widened the gap for Hispanic-White differentials[3]. Batistich and Bond (2023) find that the earlier 'Japan Shock' appears to have blunted Black wage growth in the 1970s.

[2]Adão (2016) similarly emphasizes sector-specific worker heterogeneity, showing that trade shocks can lead to unequal wage effects depending on a worker's comparative advantage across sectors.

[3]For broader context on the persistent racial wealth gap in the U.S., see Aliprantis, Carroll, and Young (2019), who document dynamic mechanisms driving Black-White disparities.

Kamal, Sundaram, and Tello-Trillo (2024) show that women in firms subject to the Family Leave Act were more likely to lay off women workers and less likely to promote them, in the face of the 'China Shock'. Pierce, Schott, and Tello-Trillo (2024) follow U.S. workers over time and find that women workers' incomes hold up better under a trade shock, while non-White workers' incomes are more likely to fall, among other heterogeneous effects. Bloom et al. (2024) add a firm-side perspective, showing that employers in high-human-capital regions were more likely to respond to the 'China Shock' by shifting away from manufacturing and reallocating toward other industries[4].

We contribute by examining how the effects of the 'China Shock' on individual U.S. workers varied by demographic group, including race, gender, marital status, parenthood, and family income — the latter of which appears to be new to the literature. As predicted by standard models, manufacturing workers and high-school dropouts are especially harmed. But several other patterns are harder to reconcile with the neoclassical adjustment paradigm. In particular, poor households face income and hours losses and attempt to adjust through industry switching, while affluent households remain more stable, avoid disruptive mobility, and even experience income gains. These results suggest that liquidity constraints, which have received little attention in the trade literature, play a central role in shaping how households respond to trade shocks. A notable exception is Giannone et al. (2023), who show that low-wealth households in Canada were more likely to move following a regional oil price shock, consistent with precautionary behavior under financial pressure.

2 Data.

Our sample of U.S. workers spans from 1988 to 2007, allowing us to isolate the impact of China's trade shock before the financial crisis. The data are drawn from the matched Current Population Survey (CPS) March Annual Social and Economic Supplement (ASEC) (Flood et al., 2021). The ASEC provides detailed income statistics, including annual earnings, sources of income, and family composition. Each respondent is surveyed during four months of one calendar year and again during the same four months of the following year. We use the Madrian and Lefgren (2000) algorithm to match individuals across years, producing a mini-panel in which each worker is observed for two years. Approximately half of the respondents can be successfully matched in this way.[5]

[4]Blanchard and Olney (2017) provide complementary evidence that export composition influences human capital accumulation through educational investment decisions.

[5]Appendix Table 1 shows that the match rate generally falls between 40 and 60 percent across years.

A key feature of the ASEC is that all labor market outcomes refer to the previous calendar year. Wage and salary income, industry of employment, usual hours worked, and work status are each reported for the year before the survey rather than the survey year itself. Thus, if a respondent was interviewed in March 2007, their reported outcomes reflect activity in 2006. We restrict the sample to individuals aged 18 to 65 who were in the labor force in the first observed year. After these restrictions, the dataset includes 478,087 observations.

The survey includes rich demographic information such as sex, age, education, marital status, number of children, and ethnicity. While the matched CPS is widely used in the labor literature (e.g., Ebenstein et al., 2014; Liu and Trefler, 2019), it introduces a well-known selection issue: individuals are most reliably matched when they remain in the same household across survey years, which tends to underrepresent movers and more transient populations. Nonetheless, the Census Bureau can follow a subset of movers, and when reasons for relocation are reported, the leading categories are housing needs (such as wanting new or better housing or to own a home), family or marital changes, and job-related factors, respectively. To assess the extent of selection, Appendix Table 2 compares matched and unmatched individuals across observable characteristics. Matched individuals are older, more likely to be married, and display greater financial security, with higher rates of affluent liquidity and lower rates of poor liquidity. They are also somewhat more likely to hold a bachelor's degree, more likely to be White and less likely to be Black, and modestly more concentrated in manufacturing, with smaller differences in family structure. Overall, these comparisons suggest modest selection into the matched sample, with matched respondents appearing somewhat more advantaged and stable than their unmatched counterparts.

To classify families as poor, middle, or affluent, we construct a liquidity index that incorporates four dimensions: income, assets, housing tenure, and participation in government assistance programs. The income component is defined relative to the official CPS poverty thresholds, which apply equivalence scales to adjust for family size and composition: families at or below twice the poverty line receive a score of 2, those between two and five times the poverty line a score of 1, and those at or above five times the poverty line a score of 0. The index sums across components and ranges from 0 to 5, with higher values indicating greater financial vulnerability. Families with a total score of 0 are classified as affluent, those with scores of 3 or higher as poor, and families with scores of 1–2 as the middle group. These cutoffs distinguish households with clear financial security from those facing multiple simultaneous constraints.

This measure captures liquidity constraints more directly than income alone, recognizing that families with limited wealth or access to credit may be less able to smooth consumption in the face of shocks. For example, a family with income more than five times the poverty line, positive asset income, and homeownership would score 0, while a renting family near the poverty line with no assets and reliance on public assistance would score 5. Focusing on the family as the financial unit avoids misclassification that could arise in households with unrelated individuals, such as roommates.

Table 1 reports descriptive statistics for the matched CPS sample. The typical respondent is in their early forties, with men and women represented in roughly equal measure, and about two-thirds are married. Manufacturing jobs account for a modest share of employment in the base year, while educational attainment varies from high school dropouts to more than a quarter with a bachelor's degree or higher. Around one in ten respondents identify as Black, and the majority as White. Our liquidity index classifies just over one-fifth of families as poor and just over one-quarter as affluent, with the remainder in the middle group.

Our measure of the trade shock is based on the NTR gap devised by Pierce and Schott (2016), which they and subsequent authors have shown to be a powerful proxy for the rise of Chinese manufacturing exports following 2001. The United States granted Permanent Normal Trade Relations (PNTR) to China in 2000, which ensured that China would face Most-Favored-Nation tariffs from the US. China's accession to the World Trade Organization (WTO) in 2001 further ensured this status.[6]

We construct two versions of the NTR gap as trade shock measures: an industry-level measure, which varies across workers based on their industry of employment, and a commuting-zone-level measure, which aggregates industry-level exposure across local labor markets using employment composition. Both measures are based on the difference between the non-NTR and NTR tariff rates for Chinese imports, as developed by Pierce and Schott (2016). The industry-level gap reflects the potential tariff increase eliminated by China's accession to the WTO, while the commuting-zone-level gap reflects the extent to which each local labor market was exposed to these tariff reductions based on its pre-shock industry mix.

The industry-level NTR gap is calculated as:

$$NTRgap_s = \frac{1}{h} \sum_h NonNTRRate_{h,s} - NTRRate_s \tag{1}$$

where s denotes the industry, and h indexes HTS 8-digit products. It measures the difference between the average non-NTR tariff and the NTR rate for Chinese imports at the eight-digit Harmonized Tariff Schedule (HTS) code. The tariff gap ranges from a decline of 20 percentage points (suitcases) to an increase of 484 percentage points (tobacco wastes),

[6]Of course, the trade war much later nullified such assurances, but that was not foreseen at the time.

with an average of 28. We first aggregate to the six-digit HTS code using a simple average, then convert to Census industry codes using a crosswalk from Autor and Dorn (2019). After aggregating to the industry level, the gap ranges from 0 (e.g., coal mining) to 63 percentage points (e.g., fabricated textiles), with a mean of 27.

Commuting zones, which encompass all metropolitan and non-metropolitan areas in the United States, are used to identify local labor markets. Commuting zones were developed by Tolbert and Sizer (1996), who used county-level commuting data from the 1990 Census to create 741 clusters of counties. These clusters characterize strong commuting ties across counties. We use Autor and Dorn (2013) to map Federal Information Processing Standards (FIPS) codes to commuting zones.[7] Our sample did not have respondents from all FIPS codes, and as a result, our matched CPS data includes 216 commuting zones.

The commuting-zone-level NTR gap is the employment-weighted average of industry gaps across a local labor market:

$$NTRgap_c = \sum_s \left(\frac{emp_{c,s}}{emp_c} \cdot NTRgap_s \right) \tag{2}$$

where c denotes the 1990 commuting zone, and $emp_{c,s}/emp_c$ is the 1999 share of CZ c's employment in industry s. Employment data come from the Census County Business Patterns (CBP) and are mapped to Census industry codes using the crosswalk by Autor and Dorn (2016).[8] The average CZ-level NTR gap is 5 percentage points, with a maximum of 22.

National employment data are reported by the Census's County Business Patterns (CBP) data. The CBP has missing data to protect the confidentiality of the respondents. We use Eckert et al. (2021) to fill in the missing data. The data are reported by Standard Industrial Classification (SIC) until 1997, and North American Industry Classification System (NAICS) for the following years. We converted the data to SIC codes using the Census's concordance. We then expanded the Autor and Dorn (2016) crosswalk to map the employment data to the Census's industry codes.

[7] Note that nine counties for Arkansas are not mapped to a commuting zone: 2010, 2068, 2105, 2195, 2198, 2230, 2232, 2275, and 2282.

[8] Employment data are originally reported in NAICS codes.

3 Empirical specification

To estimate the effect of the 'China Shock' on workers' economic outcomes, we estimate difference-in-differences regressions using the NTR gap as our treatment variable. We focus on five dependent variables that capture different dimensions of worker response: (1) an indicator for a decline in real labor income, (2) an indicator for an increase in hours worked, (3) an indicator for switching out of manufacturing, (4) an indicator for switching industries, and (5) an indicator for switching occupations.

We classify a worker as experiencing an income loss if their reported real wage and salary income falls between interviews after adjusting for inflation, excluding cases in which nominal incomes are unchanged. For hours worked, we use the CPS measure of usual weekly hours last year and define a gain as an increase between the two interviews. [9] We define a manufacturing exit as a transition from manufacturing in the first interview year to non-manufacturing in the second.[10] Industry and occupation switches are defined analogously as changes in the reported major industry or occupation between interviews, conditional on reporting positive work in the first year.[11]

Table 2 reports summary statistics for each of these outcomes by subsample. Roughly 43 percent of workers experience a decline in real income, and about 30 percent report an increase in hours worked. Income losses are somewhat less common among workers from low-income households than among those from high-income households, while hours increases are more frequent for the low-income group. Transitions out of manufacturing are similar across liquidity groups, but differences emerge on broader margins: industry and occupation switching show more variation by income level.

In what follows, we estimate the relationship between trade exposure and a worker's economic adjustment using both the industry-level and commuting-zone-level NTR gaps, as described in Section 2. Our baseline specification is a difference-in-differences regression of the form:

$$Y_{i,s,c,t} = \alpha + \beta \, \text{NTRGap}_{s \text{ or } c} \times \text{Post}_{2001} + X_i'\Gamma + \delta_t + \lambda_s + \gamma_c + \varepsilon_{i,s,c,t}, \tag{3}$$

[9]Nekoei (2022) documents that CPS respondents tend to report the median rather than the mean when asked about usual weekly hours, which may bias this measure. Because we use it only to construct a binary indicator for an increase, and apply the same calculation in both years, we do not expect the issue to systematically affect our results. We acknowledge it as a potential source of measurement error.

[10]Following the CPS 1990 industry classification, manufacturing corresponds to codes 100 through 392.

[11]Our baseline measures capture extensive-margin adjustments; Appendix Tables 3 and 4 report robustness checks using intensive-margin definitions, such as the magnitude of income loss in levels or log changes.

where the dependent variable $Y_{i,s,c,t}$ is one of five binary indicators: (1) a decline in real labor income, (2) an increase in hours worked, (3) switching out of manufacturing, (4) switching industries, or (5) switching occupations. The NTR gap is measured at either the industry or commuting-zone level and interacted with a post-2001 indicator to capture exposure to the 'China Shock'.

The control vector X_i includes age and age squared, gender, marital status, parenthood, educational attainment, race, and indicators for low- and high-income families. All specifications include year, industry, and commuting-zone fixed effects, which control for common shocks over time, permanent industry differences, and persistent local labor market characteristics. Standard errors are clustered at the level of treatment variation: either the industry or the commuting zone. In this setup, β captures whether industries or commuting zones with larger NTR gaps experienced systematically greater adjustment after 2001.

To examine whether the effect of the 'China Shock' varied across demographic groups, we estimate interaction models of the form:

$$\begin{aligned} Y_{i,s,c,t} = \alpha &+ \beta \, \text{NTRGap}_{s \text{ or } c} \times \text{Post}_{2001} \\ &+ \theta \, \text{NTRGap}_{s \text{ or } c} \times G_i + \gamma \, \text{NTRGap}_{s \text{ or } c} \times \text{Post}_{2001} \times G_i \\ &+ X_i'\Gamma + \delta_t + \lambda_s + \gamma_c + \varepsilon_{i,s,c,t}. \end{aligned} \tag{4}$$

Here G_i is an indicator for a demographic characteristic (e.g., female, parent, high-income). The coefficient γ captures how the post-2001 effect of trade exposure differs across groups. All lower-order terms, including the group dummy and its interaction with the NTR gap, are included for correct identification. Each subgroup is analyzed in a separate regression, using the same controls and fixed effects as in the baseline.

4 Findings

We proceed in three steps. First, we report industry-level results. Second, we examine commuting-zone results. Third, we draw out the overarching implications, contrasting the evidence with the neoclassical paradigm and emphasizing the role of liquidity.

Industry-level exposure

Table 3 provides the industry baseline. On average, workers in more exposed industries are less likely to report a wage loss but are more likely to switch industries and occupations.

Disaggregating in Table 4 shows that income losses are concentrated among manufacturing workers, dropouts, and households with low liquidity. Married and affluent workers, by contrast, appear relatively insulated.[12]

Hours responses provide a second lens. Table 5 shows that married workers, and to some extent Black workers, are more likely to increase hours when their industries are exposed. Workers with less education and those in manufacturing, however, are less able to do so. This echoes the household-supply channel emphasized by Nekoei and Weber (2017): some households expand hours internally, while others lack that margin.

Turning to sectoral exits, Table 6 shows that women and dropouts are disproportionately likely to leave manufacturing when their industries are exposed. Table 7 indicates that poor households are significantly more likely to switch industries, while affluent households are not. By contrast, Table 8 finds no clear pattern in occupation switching. These results suggest that liquidity-constrained households are the most likely to reallocate across industries, while better-off workers remain largely stationary.

Commuting-zone exposure

Table 9 provides the commuting-zone baseline. Here, workers in more exposed localities are more likely to increase hours, but the baseline shows little evidence of widespread wage loss. Table 10 disaggregates income losses by group: families with children are somewhat shielded, while other patterns are muted relative to the industry regressions. This suggests that direct industry shocks bite more sharply into household budgets than local exposure alone.

Table 11 shows that married and female workers expand hours most visibly in exposed commuting zones, while poor households and dropouts are far less likely to do so. The asymmetry is telling: dual-earner households can smooth shocks through hours, but liquidity-constrained and low-education workers cannot.

Turning to exits, Table 12 shows that younger workers are somewhat more likely to leave manufacturing, while families with children are less likely to do so—consistent with higher switching costs. Table 13 shows that families with children are less likely to switch industries, and Table 14 shows that affluent households are less likely to switch occupations. Manufacturing workers in exposed localities are more likely to change occupations. These results suggest that commuting-zone shocks reallocate labor more diffusely, with family structure

[12] Appendix Tables 3 and 4 show that these results do not survive under intensive-margin definitions of income loss, except for married workers. This suggests that the core patterns are concentrated on the extensive margin.

and financial buffers mediating who adjusts and how.

Interpretation

Four patterns emerge:(i) Manufacturing workers are consistently more likely to be harmed by exposure, especially in terms of income losses at the industry margin.(ii) Workers with less education, especially dropouts, are more exposed to losses and less able to compensate through hours.(iii) Married workers are comparatively cushioned, both in income and hours, reflecting the household's ability to smooth shocks internally.(iv) Liquidity-constrained households stand out as the most vulnerable. They are more likely to lose income and more likely to switch industries, yet less able to expand hours. Affluent households, by contrast, are cushioned and largely passive.

These findings partly align with the neoclassical adjustment paradigm, as in Artuç, Chaudhuri, and McLaren (2010), Dix-Carneiro (2014), or Caliendo, Dvorkin, and Parro (2019). That framework emphasizes switching costs: workers with higher costs, such as low education or family responsibilities, are expected to move less, while those with lower costs, like younger workers, should be more mobile. We find that dropouts are harmed, facing both income and hours losses and higher exit rates, while married workers are cushioned, with more stable hours and income. But the paradigm alone cannot explain the liquidity patterns: workers from poor households are more likely to experience income losses and are *less* able to compensate by raising hours, while affluent households are cushioned and therefore have little incentive to reallocate. These results point to liquidity constraints, interacting with household structure, as a central channel shaping who adjusts, on which margin, and by how much.

In short, the results support a dual explanation. Some demographic differences—marital status, family structure, and education—fit the neoclassical paradigm. But the most novel and policy-relevant patterns concern liquidity: poor households actively reallocate when possible yet remain constrained on the intensive margin, while affluent households absorb shocks passively without disruptive adjustment. It is to this liquidity-based framework that we now turn.

5 A model of labor adjustment with liquidity constraints.

Suppose that each worker/household lives for two periods and can work in either of two sectors, Traded (T) or Non-traded (NT). Workers differ in their level of human capital h, which is taken as exogenous for our purposes, and the wage w_t^j in sector j in period t is paid per unit of effective labor, which is determined by the worker's human capital. Therefore, a worker in j and period t will receive an income equal to $w_t^j h$ per hour of work. Each worker must spend a certain amount of required expenditure R in each period, which can be thought of as monthly rent payments, uncovered medical expenses, interest on past debt, and so on. Discretionary consumption in period t is denoted c_t, and provides utility $u(c_t)$, where $u(\cdot)$ is increasing, concave, and differentiable. In particular, we will focus on the example in which $u(c) \equiv \ln(c)$.

Each worker has a source of exogenous income in period t, denoted $A_t \geq 0$, which can be thought of as a proxy for the family's financial resources, which are shown to be important in the regressions.

In each period t, the worker must choose how many hours L_t to work. This can be thought of as full-time hours from a main job plus additional hours from a second job if desired. There is a disutility to work, which is given by $v(L_t)$, where $v(\cdot)$ is increasing, convex, and differentiable. In particular, we will focus on the example in which $v(L) \equiv \frac{d}{2}L^2$, where d is a positive constant. We assume for simplicity that a worker can work in only one sector per period, including any secondary jobs.[13]

Each household begins in Period 1 in one of the two sectors, and must work and earn income in that sector, and then must choose whether or not to switch to the other sector for Period 2. If the worker switches sectors, she incurs a non-pecuniary switching cost equal to κ, where $\kappa \geq 0$ is a positive constant, the same value for all households. In addition, a worker/household receives an idiosyncratic benefit ϵ^j from working for a period in sector j, and so $\mu \equiv \epsilon^j - \epsilon^i$ is an idiosyncratic cost of leaving sector j to move to sector i. Therefore, the full cost of moving is equal to $\kappa + \mu$. The realized values of ϵ^j and hence μ are learned after the decisions about Period-1 labor supply and consumption have been made, but before the decision on moving has been made. Assume that ϵ^j is a random variable with a Type-I extreme-value distribution, with parameters set so that the mean is zero, and with a volatility parameter equal to ν.

Workers have perfect foresight about the future course of aggregate variables. Assume that the labor market is under increasing pressure from import competition, so that the tradeable-sector wage is expected to fall: $w_2^T < w_1^T$. Wages in the non-traded sector are not expected to fall to the same degree, so $w_2^T < w_2^{NT}$. Consequently, the worker would benefit from switching to the non-traded sector if it were costless to do so. Workers discount

[13]It will become clear that this is not really material to the main questions of labor-supply response, which will be addressed here. For interpretation, L_t can also be thought of as effective household labor supply, so that married workers may smooth shocks partly through spousal hours.

period-2 utility at the rate $\beta < 1$. For concreteness, we will focus throughout on the case of a worker who begins in Period 1 in the tradeables sector.

Consider three contrasting situations: (i) the case of full risk sharing; (ii) the case of binding liquidity constraints; and (iii) the intermediate case of imperfect markets, in which the worker can save and borrow but cannot insure against idiosyncratic risk.

5.1 Full risk sharing.

If the worker has access to actuarially fair insurance or efficient social risk sharing as from an extended family network, she will maximize

$$\begin{aligned} u(c_1) - v(L_1) + \beta E_{\{\epsilon^T \epsilon^{NT}\}}[&\left(u(c_2^T) - v(L_2^T) + \epsilon^T\right) X(w_2^T, w_2^{NT}, \epsilon^T, \epsilon^{NT}) \\ &+ \left(u(c_2^{NT}) - v(L_2^{NT}) + \epsilon^{NT} - \kappa\right)\left(1 - X(w_2^T, w_2^{NT}, \epsilon^T, \epsilon^{NT})\right)] \end{aligned} \tag{5}$$

by choice of: Period-1 consumption and labor-supply c_1 and L_1; Period-2 consumption and labor supply c_2^j and L_2^j conditional on choice of sector j; and $X(w_2^T, w_2^{NT}, \epsilon^T, \epsilon^{NT})$, which is the sectoral choice function for Period 2, taking a value of 1 if T is chosen and zero otherwise. The budget constraint is that the expected present discounted value of consumption expenditures must be equal to the expected present discounted value of income:

$$\begin{aligned} A_1 + \frac{A_2}{1+r} + w_1^T h L_1 + \frac{m_{T,T} w_2^T h L_2^T + m_{T,NT} w_2^{NT} h L_2^{NT}}{1+r} \\ -c_1 - \frac{m_{T,T} c_2^T + m_{T,NT} c_2^{NT}}{1+r} - R - \frac{R}{1+r} = 0, \end{aligned}$$

where $m_{i,j}$ is the probability (with respect to the ϵ_j variables) that the worker if initially in sector i will choose sector j for Period 2, and r is the exogenous interest rate.

Writing the Lagrangian, taking the derivative with respect to L_1 and L_2^j, and rearranging, we find that at the optimum:

$$\frac{L_2^j}{L_1} = \frac{w_2^j}{\beta(1+r) w_1^T}.$$

The larger is the wage decline in sector j, the larger is the *reduction* in hours worked for a worker who chooses that sector. A standard benchmark case is $\beta(1+r) = 1$, in which case labor supply definitely decreases in period 2 if and only if the worker winds up in a sector with a lower wage in period 2 compared to period 1. In addition, from the first-order condition with respect to c_2^T and c_2^{NT}, consumption is the same in period 2 regardless of which sector the worker chooses, and in the case with $\beta(1+r) = 1$ it will take the same value as period-1 consumption. To sum up:

Proposition 1 *In the case of full risk sharing and no liquidity constraints, in the benchmark case with $\beta(1+r) = 1$, the household's labor supply and therefore labor income will fall if and only if the worker's wage falls, but consumption will not fall regardless of the sector chosen in period 2.*

To analyze the probability of switching sectors, first denote by $\bar{\mu}$ the critical value of μ such that in the optimal plan, the worker will switch out of the traded sector if and only if $\mu < \bar{\mu}$. The optimal switching behavior is characterised as follows:

Proposition 2 *In the case of full risk sharing and no liquidity constraints, if either A_1 or A_2 increases ceteris paribus: (i) The probability of switching out of the traded sector decreases; (ii) the probability of a drop in labor income in Period 2 weakly increases; and (iii) the probability of a rise in labor supply in Period 2 weakly decreases.*

Summary. Putting these propositions together, in the full risk sharing version of the model, an affluent worker can afford to absorb the shock: she may allow income and hours to fall without undertaking costly moves, while consumption is smoothed through risk sharing. By contrast, a poor worker cannot let consumption drop below subsistence needs and is therefore more likely to switch sectors in response to the shock. In practice, however, this switching is not always sufficient to prevent measured income losses, especially when outside options are weak. Thus, liquidity constraints shape the margins of adjustment: poorer workers scramble to preserve consumption, while affluent workers cushion shocks more passively.

5.2 The case with binding liquidity constraints.

Now, take the opposite case in which the worker cannot borrow or save to reallocate buying power across periods, and cannot share risk. In this case, each period's discretionary consumption is that period's wage income minus required consumption spending, so if the worker has chosen sector j in Period 2, we have $c_t = w_t^j h L_t^j - R$. Now, she will choose L_2^j to maximize:

$$u(w_t^j h L_t^j - R) - v(L_2^j).$$

The first-order condition is:

$$\frac{w_2^j h}{w_2^j h L_2^j - R} - dL_2^j = 0. \tag{6}$$

As long as $R > 0$, the first term of this expression is strictly decreasing in w_2^j, so that the marginal utility benefit of work is lower when the wage is higher. Taking the total derivative of (6) and solving for $\frac{\partial L_2^j}{\partial w_2^j}$ yields:

$$\frac{\partial L_2^j}{\partial w_2^j} = -\frac{hR}{\left(w_2^j h\right)^2 + d\left(c_2^j\right)^2} < 0. \tag{7}$$

In contrast to the previous case, in which reductions in the Period-2 wage resulted in a drop in the Period-2 labor supply, now a drop in the Period-2 wage can *increase* the Period-2 labor supply. The reason is that the reduced wage proposes an increase in hours worked in order to be able to meet the spending requirement R and still have some funds left over for discretionary spending c_2^j. Examining (7), we can see that the labor-supply response is larger in magnitude, the larger is R and the smaller is c_2^j. Households living paycheck to paycheck with more binding spending constraints are the ones that are most likely to feel a need to work more hours to make up for a reduction in wages. When feasible, switching into a higher-wage sector provides an alternative way to satisfy R with less reliance on additional hours.

In this situation, labor income $w_2^j h L_2^j$ can be either increasing or decreasing in the wage w_2^j, depending on the severity of the spending requirement R. First, note that the derivative of labor income with respect to the wage is equal to $hL_2^j + w_2^j h \frac{\partial L_2^j}{\partial w_2^j}$. One extreme case is where R is large enough that discretionary spending c_2^j becomes vanishingly small, in which case the household to a close approximation is merely setting L_t^j at the value that meets the spending constraint R exactly, or $L_t^j = \frac{R}{w_2^j h}$. In this case, the derivative of labor supply with respect to the wage is equal to $-\frac{hR}{\left(w_2^j h\right)^2}$, which is exactly the value of (7) in the limit. Clearly, in this case, labor income is unaffected by changes in the wage. On the other hand, if $R = 0$, labor supply is $L_2^j = 1$ regardless of the wage, and consequently, as (7) confirms, as R becomes small, the labor-supply response becomes arbitrarily close to zero. In this case, labor income is strictly increasing in the wage. These observations can be summarized as follows.

Proposition 3 *In the case of liquidity constraints with positive required spending, labor supply in each state is a strictly decreasing function of the wage in that state. Labor income is increasing in the wage in each state, but if the required spending is sufficiently large, the effect of the wage on labor income will be vanishingly small.*

Proof: In appendix.

In contrast to the full risk-sharing case, in this case, labor supply curves (so to speak) are upward sloping in each period.

Proposition 4 *In the case of liquidity constraints with positive required spending, in the limit as $A_1, A_2, h \to 0$, labor income in both periods takes a limit of R, and the probability of switching sectors takes a limit of 1. In addition, if $w_2^{NT} > w_1^T$, in the limit labor supply in Period 2 almost surely is lower than the labor supply in Period 1.*

Summary. Under binding liquidity constraints the household is primarily focused on meeting the spending requirement R. In principle this can occur either by raising hours at the current wage or by switching into a higher-wage state. In practice, however, constrained households often face limited opportunities to expand labor supply or to find better jobs quickly; as a result they tend to suffer income losses and may be forced to exit manufacturing or accept lower-paid employment. Switching remains a possible response, but when it occurs it is frequently associated with search costs or temporary non-employment and therefore does not necessarily prevent an observed fall in measured income.

The contrast with the full-insurance case is instructive. With full insurance a poor worker would switch mainly to preserve consumption, and hours respond according to substitution effects. Under binding liquidity constraints, by contrast, the hours response is endogenous to available outside options: constrained households often cannot raise hours sufficiently or access better jobs quickly enough, so measured outcomes show larger income losses and more disruptive exits.

5.3 The case with imperfect markets.

Now, suppose that the worker starts Period 1 with initial financial assets given by A_1 and can borrow or lend at the market interest rate r but cannot insure against idiosyncratic risks. In this case, she can prepare for a Period-2 shock only by saving in Period 1. Since with log utility $u''' > 0$, there is a precautionary motive for saving, which also implies a precautionary motive for Period-1 labor supply.

The budget constraint in this case depends on the realized state. In the event that the realized values of ϵ^T and ϵ^{NT} lead the worker to choose sector j for Period 2, the budget constraint is:

$$c_1 + \frac{c_2^j}{1+r} + R + \frac{R}{1+r} = A_1 + \frac{A_2}{1+r} + w_1^T h L_1^T + \frac{w_2^j h L_2^j}{1+r}. \tag{8}$$

The worker works and consumes in Period 1, resulting in savings equal to $s = A_1 + w_1^T hL_1 - R - c_1$ and beginning-of-Period-2 financial resources equal to $A^* \equiv A_2 + (1+r)s = A_2 + (1+r)(A_1 + w_1^T hL_1 - R - c_1)$. Then the worker learns the value of ϵ^j and decides which sector to choose for Period 2. Note that although for this simple, stylized model we are assuming that the values w_2^j are known with certainty from the beginning, there is still idiosyncratic risk, because the idiosyncratic values ϵ^j could induce the worker to choose the lower-wage sector.

The worker must maximize lifetime utility (5) subject to the two constraints (8). The first-order constraints yield:

$$\frac{v'(L_1^T)}{w_1^T} = \beta(1+r)E_\epsilon\left[\frac{v'(L_2^j)}{w_2^j}\right]. \tag{9}$$

This is a standard Euler condition for labor supply (of course there is a corresponding condition for consumption). Clearly, in the benchmark case with $\beta(1+r) = 1$, if $w_2^T = w_2^{NT} < w_1^T$, this condition predicts that Period-2 labor supply will be below Period-1 labor supply. Hours worked will drop over time as the local wage drops due to import competition. More generally, the Euler condition shows that since in that case $w_2^j < w_1^T$ for both sectors j, we must have $L_2^j < L_1^T$ for at least one j.

However, if the Period-2 wages in the two sectors are not the same, there is the possibility of an increase in hours worked in the second period for one of the two sector outcomes. The Period-2 portion of the optimization can be separately analyzed, conditional on A^*. The Period-2 labor supply will maximize $u(A^* + w_2^j hL_2^j - R) - v(L_2^j)$. Rearranging the total derivative of the first-order condition yields:

$$\frac{\partial L_2^j}{\partial w_2^j} = \frac{h(A^* - R)}{\left(w_2^j h\right)^2 + d\left(c_2^j\right)^2}. \tag{10}$$

Period-2 labor supply is increasing in the wage if $A^* > R$ and decreasing otherwise. The usual income and substitution effects are at work. If assets saved from the previous period are enough to cover required spending, the substitution effect dominates and labor supply is upward-sloping, otherwise, the income effect dominates so that labor supply is downward-sloping. (If $A^* = R$, labor supply is $L_2^j = d^{-1/2}$ regardless of the wage.) Of course, the value A^* is endogenous, with higher-h workers generally saving more. If the worker in Period 1 cannot afford to save enough to cover Period-2 required spending, then (7) shows that if the worker winds up in the sector with the lower wage, she will choose a higher labor supply, and it is possible that $L_2^T > L_1^T$.

This can all be summarized as follows.

Proposition 5 *Proposition 3. Let $\beta(1 + r) = 1$. (i) In the case with imperfect markets, where the worker can save and borrow but cannot insure against idiosyncratic risk, if $w_2^j < w_1^T$ for both sectors j, the Period-2 labor supply must be lower than the Period-1 labor supply in at least one state.*

(ii) The set of parameter values for which $L_2^T > L_1^T$ is non-empty.

(iii) Holding other parameter values fixed, if A_1, A_2, or h is sufficiently large, then labor supply is lower in Period 2 than in Period 1, regardless of the chosen sector.

Proof. Part (i) was derived above. Parts (ii) and (iii) are proven in the Appendix.

5.4 Comparison of the three cases.

How a worker responds to a trade shock depends critically on access to consumption-smoothing and risk-sharing instruments. With good access to financial instruments, as in Section 5.1, households can smooth intertemporally and reduce labor supply when wages fall, allocating effort to states with higher returns. By contrast, when financial instruments are unavailable, as in Section 5.2, constrained households face stark tradeoffs: reducing hours would sharply lower consumption, so the household must either raise hours or attempt a sector switch to meet required spending. The intermediate case with borrowing and saving but no insurance, as in Section 5.3, yields ambiguous outcomes that depend on precautionary saving and realized shocks.

Propositions 2 and 4 guide interpretation of the empirical facts. When liquidity constraints bind and required spending is positive, poor households face a high risk of income loss because they cannot readily smooth or expand effective labor supply. In many cases, constrained households end up exiting manufacturing or switching industries, but these moves often come with search costs or spells of lower measured income. Affluent households, by contrast, possess greater financial buffers and can therefore better cushion the shock: they are less likely to suffer large income declines, more likely to maintain hours, and less likely to undertake disruptive sector or occupation switches. Put differently, liquidity constraints tend to amplify exposure for poor households rather than enable compensating adjustments, while affluent households smooth passively and bear smaller measured losses. This pattern is what the regressions in Tables 4, 7, 11 and 14 document.

In the case of binding liquidity constraints, poorer workers are more likely to suffer an income loss and to exit manufacturing, but are less able to offset these losses by increasing hours. Liquidity constraints thus amplify exposure rather than enabling compensation. By contrast, affluent households are more likely to cushion shocks: they experience smaller income losses, maintain hours, and are less likely to make disruptive sector or occupation switches. This pattern is consistent with what we find in the regressions.

6 Conclusions.

We have examined how workers adjust to trade shocks in U.S. labor markets using the matched CPS. Some of our results fit naturally within the neoclassical adjustment paradigm. Manufacturing workers, for example, are more likely to suffer income losses when their industries are hit, while married workers appear able to cushion shocks by adjusting hours. These findings are consistent with the idea that switching costs vary across demographic groups and shape exposure to import competition.

The most novel and striking patterns, however, concern family income. Workers from poor households are more likely to experience income losses and to respond through disruptive reallocation, while workers from affluent households are relatively cushioned, less likely to see income losses and less likely to switch industries or occupations. These differences are difficult to reconcile with switching costs alone. They are more naturally explained by liquidity constraints: poor households, unable to smooth consumption, must scramble to preserve income, while affluent households can afford to absorb shocks more passively.

This suggests that an important dimension has been missing from much of the trade and labor adjustment literature. Existing models emphasize switching costs and mobility frictions but rarely account for household liquidity. Our results highlight that the ability or inability to smooth consumption in the face of shocks is central to understanding who bears the losses from trade and how adjustment occurs.

7 Appendix.

Proof of Proposition 2. First, if we define the maximized value in (5) subject to the budget constraint by $U(A)$, where $A \equiv A_1 + \frac{A_2}{(1+r)}$, then clearly $U'(A) = \lambda$, where λ is the Lagrange multiplier on the budget constraint. Further, the function U is concave. For any two values of A, say, $A' \neq A''$, and any value $\sigma \in (0,1)$, if we denote the optimal choices of consumption, labor supply, and sector choice for A' and A'' with primes and double primes respectively, then for $A = \sigma A' + (1-\sigma)A''$ feasible choices would be consumption of $c_t^j = \sigma(c_t^j)' + (1-\sigma)(c_t^j)''$, $L_t^j = \sigma(L_t^j)' + (1-\sigma)(L_t^j)''$, and $X = \sigma(X)' + (1-\sigma)(X)''$ (where the latter is interpreted as a probability of switching in the event that $X'(w_2^T, w_2^{NT}, \epsilon^T, \epsilon^{NT}) \neq X''(w_2^T, w_2^{NT}, \epsilon^T, \epsilon^{NT})$). The realized lifetime utility from those feasible choices will be greater than $\sigma U(A') + (1-\sigma)U(A'')$, due to the concavity of $u(\cdot)$ and the convexity of $v(\cdot)$. Therefore, $U(\sigma A' + (1-\sigma)A'') > \sigma U(A') + (1-\sigma)U(A'')$, so the function $U(\cdot)$ is strictly concave, and so $U'(A)$ is decreasing in A. Consequently, an increase in either A_1 or A_2 will lower the Lagrange multiplier λ.

Next, the first-order condition for labor supply is:

$$v'(L_t^j) = \lambda w_t^j h, \tag{11}$$

which, given our functional-form assumptions, amounts to $L_t^j = \frac{\lambda w_t^j h}{d}$. Since we know that consumption is the same in both periods and states, we can denote it as c, and we can subtract ϵ^{NT} from the interior of the expectations operator in (5) to write idiosyncratic shocks in terms of μ. We can then write (5) as:

$$(1+\beta)u(c) - v(L_1^T) - \beta\left(\int_{\bar{\mu}}^{\infty} v(L_2^T)f(\mu)d\mu + \int_{-\infty}^{\bar{\mu}} (v(L_2^{NT}) + \mu + \kappa)f(\mu)d\mu\right), \tag{12}$$

where $\bar{\mu}$ is a choice variable such that the worker switches sectors in and only if $\mu < \bar{\mu}$ and $f(\cdot)$ is the density for μ. Then the term $m_{T,T}$ in the budget constraint is equal to $\int_{\bar{\mu}}^{\infty} f(\mu)d\mu$ and $m_{T,NT} = 1 - m_{T,T}$. Taking the first-order condition with respect to $\bar{\mu}$ gives:

$$v\left(L_2^{NT}\right) - v\left(L_2^T\right) + \bar{\mu} + \kappa = \lambda\left(w_2^{NT} h L_2^{NT} - w_2^T h L_2^T\right). \tag{13}$$

Re-arranging, using $L_t^j = \frac{\lambda w_t^j h}{d}$, turns this into:

$$\bar{\mu} + \kappa = \frac{\lambda^2 h^2}{d}\left[\left(w_2^{NT}\right)^2 - \left(w_2^T\right)^2\right]. \tag{14}$$

Clearly, this implies that if λ falls, then $\bar{\mu}$ falls as well. Given the concavity finding above, this proves the first result: An increase in A_1 or A_2 results in a lower value of λ, and therefore a lower value of $\bar{\mu}$, and so a reduced probability of switching sectors.

For the second result, if $w_2^{NT} < w_1^T$, the worker will see a drop in income whether or not she switches sectors, but if $w_2^{NT} > w_1^T$, the worker will see a drop in income if and only if she stays in the traded sector, and the probability of that event is, as we just established, increasing in A_1 and A_2. The third result follows from the findings on labor supply. **Q.E.D.**

Proof of Proposition 3. The only portion requiring proof is the effect of the wage on labor income within each state. Labor income is increasing in the wage if the elasticity of labor-supply with respect to the wage implied by (7) is less than unity in absolute value. That elasticity can be written as:

$$\frac{w_2^j}{L_2^j}\frac{\partial L_2^j}{\partial w_2^j} = -\frac{w_2^j hR/L_2^j}{\left(w_2^j h\right)^2 + d\left(c_2^j\right)^2} > -\frac{w_2^j hR/L_2^j}{\left(w_2^j h\right)^2} = -\frac{R}{w_2^j h L_2^j} > -1. \tag{15}$$

This confirms that the elasticity is less than unity in absolute value, so labor income is increasing in the wage.

Proof of Proposition 5.

To analyze the two-period maximization problem, it is useful to break it into single-period pieces. Define:

$$V(A, w, h, R) \equiv \max_L \{u(whL + A - R) - v(L)\}.$$

The first-order condition for this maximization is:

$$whu'(c) = v'(L), \text{ or } \frac{wh}{A + whL - R} - dL = 0, \tag{16}$$

where $c \equiv A + whL - R$ is consumption. If we denote the optimal value of labor supply and consumption in this problem by $L^*(A, w, h, R)$ and $c^*(A, w, h, R)$ respectively, then from the total derivatives of the first-order condition we can derive:

$$\frac{\partial L^*}{\partial w} = \frac{h(A - R)}{(wh)^2 + d\,(c)^2} \tag{17}$$

$$\frac{\partial L^*}{\partial h} = \frac{w(A - R)}{(wh)^2 + d\,(c)^2} \tag{18}$$

$$\frac{\partial L^*}{\partial A} = \frac{-wh}{(wh)^2 + d\,(c)^2} < 0. \tag{19}$$

The last condition shows that $\left(wh\frac{\partial L^*}{\partial A}\right) \in (0,1)$, so that a one-dollar increase in initial funds leads to less than a one-dollar drop in labor income, and therefore an increase in consumption:

$$\frac{\partial c^*}{\partial A} = \frac{d\,(c)^2}{(wh)^2 + d\,(c)^2} \in (0,1). \tag{20}$$

The Envelope Theorem ensures that:

$$\frac{\partial V}{\partial A} = u'(c^*) = \frac{1}{c^*} = \frac{1}{A + whL^* - R} > 0. \tag{21}$$

Condition (20), then, ensures that $\frac{\partial^2 V}{\partial A^*} < 0$.

Now, with this single-period maximized utility function V, we can characterize the two-period maximization problem as:

$$\max_s \left(V(A_1 - s, w_1^T, h, R) + \beta E_\epsilon \max_j \{V((1+r)s, w_2^j, h, R) + \epsilon^j\} \right), \tag{22}$$

where the expectation is taken with respect to the ϵ^j. The first-order condition is:

$$u'(c_1) = \beta(1+r)E_j u'(c_2^j), \tag{23}$$

or in other words,

$$\frac{1}{A_1 - s + w_1^T h L_1^T - R} = \beta(1+r)E_j \left[\frac{1}{(1+r)s + w_2^j h L_2^j - R}\right], \tag{24}$$

where the expectation is taken with respect to the choice of sector in Period 2.

Claim (ii): There exist values of the parameters for which $L_2^T > L_1^T$.

Proof. Given the distributional assumption on ϵ^j, the probability that the worker chooses sector NT for period 2 can be written as:

$$\rho(A^*, \nu) = \frac{\exp(V(A^*, w_2^{NT}, h, R)/\nu)}{\exp(V(A^*, w_2^{NT}, h, R)/\nu) + \exp(V(A^*, w_2^T, h, R)/\nu)} \tag{25}$$

$$= \frac{1}{1 + \exp((V(A^*, w_2^T, h, R) - V(A^*, w_2^{NT}, h, R))/\nu)}, \tag{26}$$

written as a function of $A^* = (1+r)s$, the savings available in Period 2. Fix w_1^T, h, β, r, and R, and set $A_1 = 0$, $w_2^{NT} = w_1^T$, and $\beta(1+r) = 1$. Consider a sequence of parameter values

$(w_2^T(n), \nu(n))$, indexed by $n = 1, 2, \ldots$, as follows. For each n, choose $w_2^T(n) \in (0, 1/n)$. Denote the value of savings and second-period traded-sector labor supply for each n as $s(n)$ and $L_2^T(n)$, respectively.

For a given n, we can choose a sequence of values for ν, say $\tilde{\nu}(n,k)$, $k = 1, 2, \ldots$, such that $\tilde{\nu}(n,k) \to 0$ as $k \to \infty$. For such a sequence, since $w_2^T < w_2^{NT}$, the function $\rho((1+r)s)$ will converge uniformly to a function that takes a value of unity for all values of s.

Define $W^j(s) \equiv V(A_1 - s, w_1^T, h, R) + \beta V((1+r)s, w_2^j, h, R)$ for $j = \{T, NT\}$. In Period 1 the worker will choose s to maximize:

$$W(s; n, k) \equiv \rho((1+r)s, \nu(n,k))W^{NT}(s) + (1 - \rho((1+r)s, \nu(n,k)))W^T(s).$$

Since $w_2^{NT} = w_1^T$, the function $W^{NT}(s)$ is maximized at $s = 0$. Consequently, the value of s, say $s(n,k)$, that maximizes $W(s; n, k)$ will follow $s(n,k) \to 0$ as $k \to \infty$. Choose a value of k high enough that $s(n,k) < 1/n$, and then set $\nu(n) = \tilde{\nu}(n,k)$ and denote the resulting savings level as $s(n)$.

Given these choices, as $n \to \infty$ the minimum labor effect for a worker in sector T in Period 2 in order to meet the spending requirement R is:

$$\frac{(R - (1+r)s(n))}{w_2^T(n)h},$$

which grows without bound since $s(n) \to 0$ and $w_2^T(n) \to 0$ as $n \to \infty$. Therefore, for high enough n, $L_2^T(n) > L_1^T$. *QED.*

Claim (iii): Holding other parameter values fixed, if A_1 or h is sufficiently large, then labor supply is lower in Period 2 than in Period 1 regardless of the chosen sector.

To show this claim, we first need two preliminary claims:

Claim (iii)(a): If $A^* \geq R$, then $L_2^j < L_1^T$ for $j = T, NT$.

Proof. Suppose that $A^* \geq R$. Since $w_2^{NT} > w_2^T$, consumption is greater in Period 2 in the NT sector than in the T sector. (By (17), labor-supply will be higher in the NT sector in Period 2 than in the T sector, so labor income will also be higher in that sector and therefore consumption.) Therefore, $u'(c_2^{NT}) < u'(c_2^T)$, and by (16), $\frac{v'(L_2^{NT})}{w_2^{NT}} < \frac{v'(L_2^T)}{w_2^T}$. By (9), we must have $\frac{v'(L_2^j)}{w_2^j}$ higher than $\frac{v'(L_1^T)}{w_1^T}$ for one value of j and lower for the other value of j, so $\frac{v'(L_2^{NT})}{w_2^{NT}} < \frac{v'(L_1^T)}{w_1^T}$. Since $w_2^{NT} < w_1^T$, this implies that $L_2^{NT} < L_1^T$. Further, by (17), $L_2^T < L_2^{NT}$, so labor supply is lower in Period 2 in both states than in Period 1. *QED.*

Claim (iii)(b): Holding other parameter values constant, if either A_1 or h is large enough, then $L_1^T > L_2^j$ for $j = T, NT$.

Proof. First consider A_1. We will show that for sufficiently high values of A_1, the optimal value of savings s will be such that $(1+r)s = A^* > R$. Suppose the contrary, so that we can find a sequence of values of A_1, say $A_1(n)$ for $n = 1, 2, \ldots$, such that $A_1(n) \to \infty$ and $(1+r)s(n) \leq R$ for all n, where $s(n)$ is the savings level associated with $A_1(n)$. In this case, we can use the one-period optimization problem (7) to study the first-period outcomes, where A takes the value $A_1(n) - s(n)$. Denoting the optimal labor supply in the first period associated with $A_1(n)$ by $L_1^T(n)$, the first-order condition (16) shows that $L(n) \to 0$. Now, the second-period outcomes can be studied with (7), where A takes the value $(1+r)s(n) \leq R$ for all n. If $A = R$, (16) shows that $L = d^{-1/2}$, so $A \leq R$ implies that $L_2^j(n) \geq d^{-1/2}$ for $j = T, NT$. Consequently, for high enough n the labor-supply Euler condition (9) will fail.

This establishes the claim that for A_1 large enough $A^* > R$. But then the previous claim (iii)(a) shows that for large enough A_1 we will have $L_2^j < L_1^T$ for $j = T, NT$.

We now turn to the case of large h. Suppose that we can find a sequence $h(n)$ such that $h(n) \to \infty$ and $(1+r)s(n) \leq R \forall n$. Analogously to the above, (16) shows that $L_1(n), L_2^j(n) \to d^{-1/2}$. As a result, denoting consumption in Period 1 and 2 by $c_1(n)$ and $c_2^j(n)$ for each value of n respectively,

$$c_1(n)/c_2^j(n) = \frac{A_1 - s(n) + w_1^T h(n) L_1^T(n) - R}{(1+r)s(n) + w_2^j h(n) L_2^j(n) - R} \to \frac{w_1^T}{w_2^j} > 1$$

for $j = T, NT$. Consequently, for high enough n, the Euler condition for consumption (23) will fail.

Therefore, for large enough h, we will have $A^* > R$ and $L_1^T > L_2^j$ for $j = T, NT$. This establishes Claim (iii). *QED.*

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Table 1: Summary Statistics: Matched CPS Sample

Variable	**Mean**	**Standard Deviation**
Age (years)	41.25	11.62
Female	0.483	0.500
Married	0.671	0.470
Has child in family	0.471	0.499
Bachelor's degree or more	0.274	0.446
High school dropout	0.101	0.301
Manufacturing worker	0.150	0.357
Black	0.088	0.283
White	0.859	0.348
Poor (liquid)	0.206	0.404
Affluent (liquid)	0.273	0.446

Notes: This table reports summary statistics for the matched CPS sample (1989–2008). The sample is restricted to individuals aged 19–66 who are in the labor force and report an industry. Observations are matched across survey years using the Madrian and Lefgren (2000) algorithm, with additional consistency checks on sex, race, and age. "Poor (liquid)" and "Affluent (liquid)" capture financial constraints based on a family liquidity index that incorporates income, assets, homeownership, and program participation. Educational attainment, marital status, parenthood, and manufacturing employment are measured in the first year of observation.

Table 2: Summary Statistics for Dependent Variables, by Income Group

Group	**Wage Loss**	**Hours Increase**	**Leave Mfg.**	**Switch Industry**	**Switch Occupation**
Full Sample	0.429	0.296	0.036	0.431	0.516
	(0.495)	(0.457)	(0.187)	(0.495)	(0.500)
Low-Income	0.395	0.343	0.038	0.506	0.588
	(0.489)	(0.475)	(0.191)	(0.500)	(0.492)
Medium-Income	0.420	0.287	0.036	0.426	0.515
	(0.493)	(0.452)	(0.185)	(0.494)	(0.500)
High-Income	0.474	0.280	0.036	0.383	0.465
	(0.499)	(0.449)	(0.186)	(0.486)	(0.499)

Notes: This table reports means and standard deviations (in parentheses) of binary dependent variables used in the analysis, by household income group. The number of observations is: Full Sample = 478,087; Low-Income = 98,423; Medium-Income = 248,958; High-Income = 130,706. "Wage loss" is an indicator for a year-over-year decline in real labor income. "Hours increase" indicates an increase in total annual hours worked. "Leave manufacturing" is an indicator for transitioning from a manufacturing to a non-manufacturing industry. "Switch industry" and "switch occupation" indicate whether the individual transitioned to a new industry or occupation, respectively. Income groups are defined by commuting-zone per-capita household income. All income values are CPI-adjusted to 1999 dollars.

Table 3: Baseline Model: NTR Gap (Industry)

	(1)	**(2)**	**(3)**	**(4)**	**(5)**
	Wage Loss	Hours Increase	Leave Mfg.	Switch Industry	Switch Occupation
NTR Gap × Post-2001	-0.030^{**}	0.024	0.044	0.067^{**}	0.076^{***}
	(-2.12)	(1.55)	(0.94)	(2.15)	(3.39)
Observations	470,927	470,927	71,059	470,776	470,927
R^2 (within)	0.0114	0.0063	0.0099	0.0157	0.0184

Notes: Dependent variables are shown in the column headers. Column (3) restricts the sample to individuals in manufacturing in the base year. All regressions include year dummies, industry, and commuting-zone fixed effects. Standard errors are clustered at the industry level; the number of clusters varies by column due to sample restrictions. Controls in all specifications include age and age squared, female, married, at least one child, bachelor's degree, high-school dropout, and household-level low- and high-income dummies constructed using an equivalence-scale definition. The main effect of the continuous treatment (NTR Gap) is omitted due to collinearity with fixed effects. t statistics in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 4: Income Loss and NTR Gap (Industry): Heterogeneity by Subgroups

	Dropout	Bachelor	Female	Manufacturing	Young	Old	Married	Kids	Poor	Affluent	Black	White
NTR × Post	-0.030^{**}	-0.013	-0.024	-0.449^{***}	-0.039^{**}	-0.034^{**}	0.037	-0.031	-0.040^{**}	-0.012	-0.032^{**}	-0.021
	(-1.99)	(-0.72)	(-1.33)	(-3.67)	(-2.57)	(-2.25)	(1.44)	(-1.55)	(-2.65)	(-0.72)	(-2.13)	(-0.71)
Group (=1)	0.055^{***}	-0.055^{***}	0.018^{***}	–	-0.030^{***}	0.032^{***}	-0.027^{***}	0.018^{***}	-0.055^{***}	0.079^{***}	0.039^{***}	-0.016^{***}
	(14.78)	(-15.76)	(3.71)	–	(-6.94)	(5.24)	(-8.02)	(7.53)	(-15.47)	(21.92)	(7.45)	(-3.17)
NTR × Group	0.004	-0.012	-0.016	–	-0.060^{***}	0.036	0.042^{**}	-0.005	-0.018	0.027	-0.004	0.010
	(0.18)	(-0.54)	(-0.78)	–	(-2.87)	(1.24)	(2.57)	(-0.25)	(-0.88)	(1.43)	(-0.15)	(0.44)
NTR × Post × Group	0.003	-0.056^{*}	-0.012	0.476^{***}	0.075^{*}	0.025	-0.093^{***}	0.001	0.045^{*}	-0.069^{**}	0.024	-0.010
	(0.07)	(-1.67)	(-0.34)	(3.79)	(1.87)	(0.65)	(-3.30)	(0.04)	(1.78)	(-2.19)	(0.51)	(-0.27)
Observations						470,927						
R^2 (within)						0.0114						

Notes: Each column reports a separate regression of income loss on Post_t, $\text{NTR}_{\text{ind}} \times \text{Post}_t$, a subgroup indicator (Group), $\text{NTR}_{\text{ind}} \times \text{Group}$, and the triple interaction $\text{NTR}_{\text{ind}} \times \text{Post}_t \times \text{Group}$. Controls include age and age squared; female; married; at least one child; bachelor's degree; high-school dropout; and low- and high-income dummies. All regressions absorb commuting-zone, industry, and year fixed effects; SEs clustered by industry. For the Manufacturing subgroup, the level Group effect and NTR × Group are absorbed; the triple remains identified. t statistics in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 5: Hours Increase (Indicator) and NTR Gap (Industry): Heterogeneity by Subgroups

	Dropout	Bachelor	Female	Manufacturing	Young	Old	Married	Kids	Poor	Affluent	Black	White
NTR × Post	0.033^{**}	0.015	0.035^{*}	0.146^{**}	0.015	0.020	-0.008	0.012	0.027^{*}	0.026	0.018	0.053^{*}
	(2.19)	(0.97)	(1.95)	(2.50)	(0.99)	(1.16)	(-0.41)	(0.68)	(1.72)	(1.58)	(1.14)	(1.82)
Group (=1)	-0.002	0.028^{***}	0.029^{***}	–	-0.027^{***}	-0.028^{***}	0.010^{***}	0.015^{***}	0.052^{***}	-0.008^{***}	0.002	0.004
	(-0.44)	(6.37)	(5.84)	–	(-6.63)	(-5.29)	(2.91)	(4.27)	(11.63)	(-3.01)	(0.25)	(0.90)
NTR × Group	-0.036	0.080^{***}	-0.053^{**}	–	-0.103^{***}	0.018	0.034^{*}	-0.038^{**}	-0.102^{***}	0.104^{***}	-0.077^{***}	0.058^{**}
	(-1.30)	(3.35)	(-2.28)	–	(-3.48)	(0.73)	(1.97)	(-2.06)	(-4.42)	(6.33)	(-2.89)	(2.39)
NTR × Post × Group	-0.077^{**}	0.005	-0.035	-0.152^{**}	0.048	0.020	0.045^{*}	0.025	-0.007	-0.007	0.079^{*}	-0.033
	(-2.34)	(0.18)	(-1.54)	(-2.21)	(1.39)	(0.58)	(1.79)	(1.37)	(-0.25)	(-0.26)	(1.81)	(-1.06)
Observations						470,927						
R^2 (within)						0.0063–0.0065						

Notes: Each column reports a separate regression of the hours-increase indicator on Post_t, $\text{NTR}_{\text{ind}} \times \text{Post}_t$, a subgroup indicator (Group), $\text{NTR}_{\text{ind}} \times \text{Group}$, and the triple interaction $\text{NTR}_{\text{ind}} \times \text{Post}_t \times \text{Group}$. Controls and fixed effects as in Table 16; SEs clustered by industry. For the Manufacturing subgroup, the Group and NTR×Group are absorbed; the triple remains identified. t statistics in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 6: Leaving Manufacturing and NTR Gap (Industry): Heterogeneity by Subgroups (Restricted to Baseline Manufacturing Workers)

	Dropout	Bachelor	Female	Manufacturing	Young	Old	Married	Kids	Poor	Affluent	Black	White
NTR × Post	0.016	0.031	0.010	–	0.043	0.054	−0.011	0.003	0.044	0.055	0.048	0.042
	(0.33)	(0.68)	(0.22)	–	(0.94)	(1.18)	(−0.13)	(0.04)	(1.00)	(1.12)	(0.59)	(0.59)
Group (=1)	0.027	0.010	0.040**	–	0.017	−0.019	0.001	−0.014	0.079***	−0.061***	0.022	−0.003
	(1.20)	(0.71)	(2.48)	–	(1.28)	(−1.21)	(0.07)	(−1.74)	(4.71)	(−4.37)	(1.17)	(−0.19)
NTR × Group	−0.207***	0.148***	−0.109**	–	−0.014	−0.034	−0.012	−0.015	−0.164***	0.178***	−0.046	0.056
	(−2.74)	(3.17)	(−2.26)	–	(−0.44)	(−1.00)	(−0.38)	(−0.53)	(−3.00)	(3.84)	(−0.82)	(1.34)
NTR × Post × Group	0.124*	0.015	0.088*	–	−0.001	−0.072	0.078	0.086*	0.012	−0.051	−0.048	0.002
	(1.78)	(0.18)	(1.88)	–	(−0.02)	(−1.40)	(1.18)	(1.82)	(0.19)	(−0.87)	(−0.43)	(0.03)
Observations	71,059											
R^2 (within)	0.0099–0.0105											

Notes: Each column reports a separate regression of an indicator for leaving manufacturing on Post_t, $\text{NTR}_{\text{ind}} \times \text{Post}_t$, a subgroup indicator (Group), $\text{NTR}_{\text{ind}} \times \text{Group}$, and the triple interaction $\text{NTR}_{\text{ind}} \times \text{Post}_t \times \text{Group}$. Sample restricted to baseline manufacturing workers. Controls and fixed effects as above; SEs clustered by industry. For Manufacturing, Group and NTR × Group are absorbed; the triple remains identified. t statistics in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 7: Leaving Industry and NTR Gap (Industry): Heterogeneity by Subgroups

	Dropout	Bachelor	Female	Manufacturing	Young	Old	Married	Kids	Poor	Affluent	Black	White
NTR × Post	0.051*	0.076**	0.059*	0.008	0.059*	0.071*	0.049	0.044	0.060*	0.070*	0.059*	0.137**
	(1.65)	(2.31)	(1.89)	(0.14)	(1.89)	(1.91)	(1.05)	(1.21)	(1.96)	(1.96)	(1.96)	(2.53)
Group (=1)	0.013	−0.024*	0.039***	–	−0.000	−0.025***	−0.004	−0.012***	0.058***	−0.033***	0.031***	−0.044***
	(1.37)	(−1.81)	(3.75)	–	(−0.09)	(−2.89)	(−1.25)	(−4.22)	(10.71)	(−7.27)	(3.20)	(−5.39)
NTR × Group	−0.086*	0.217***	−0.077*	–	−0.064**	−0.021	0.030	−0.005	−0.066*	0.083***	−0.133***	0.130***
	(−1.67)	(4.29)	(−1.77)	–	(−2.44)	(−0.65)	(1.50)	(−0.21)	(−1.76)	(2.62)	(−3.51)	(4.61)
NTR × Post × Group	0.099**	−0.094**	0.012	0.072	0.020	−0.031	0.025	0.045	0.092***	−0.010	0.091	−0.080*
	(2.05)	(−2.25)	(0.37)	(0.80)	(0.46)	(−0.92)	(0.73)	(1.39)	(3.07)	(−0.27)	(1.63)	(−1.83)
Observations	470,776											
R^2 (within)	0.0157–0.0160											

Notes: Each column reports a separate regression of an indicator for leaving industry on Post_t, $\text{NTR}_{\text{ind}} \times \text{Post}_t$, a subgroup indicator (Group), $\text{NTR}_{\text{ind}} \times \text{Group}$, and the triple interaction $\text{NTR}_{\text{ind}} \times \text{Post}_t \times \text{Group}$. Controls and fixed effects as in prior tables; SEs clustered by industry. For Manufacturing, Group and NTR × Group are absorbed; the triple is identified. t statistics in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 8: Different Occupation and NTR Gap (Industry): Heterogeneity by Subgroups

	Dropout	Bachelor	Female	Manufacturing	Young	Old	Married	Kids	Poor	Affluent	Black	White
NTR × Post	0.074***	0.080***	0.053*	0.192	0.070***	0.085***	0.086***	0.070***	0.063***	0.093***	0.073***	0.133***
	(3.44)	(3.07)	(1.84)	(1.40)	(2.96)	(3.83)	(2.63)	(2.76)	(2.96)	(3.94)	(3.07)	(3.14)
Group (=1)	0.001	−0.048***	0.061***	–	−0.005	−0.034***	−0.009***	−0.010**	0.051***	−0.035***	0.048***	−0.017**
	(0.23)	(−3.93)	(5.85)	–	(−0.96)	(−4.53)	(−2.93)	(−2.56)	(9.37)	(−8.80)	(5.49)	(−2.56)
NTR × Group	0.003	0.061	−0.110***	−0.207	0.001	−0.002	−0.004	−0.029	0.017	0.008	0.003	0.021
	(0.06)	(1.48)	(−2.64)	(−1.43)	(0.05)	(−0.06)	(−0.20)	(−1.61)	(0.49)	(0.26)	(0.09)	(0.83)
NTR × Post × Group	0.031	−0.030	0.033	−0.207	0.041	−0.066*	−0.015	0.014	0.059	−0.063	0.042	−0.067*
	(0.67)	(−0.70)	(0.86)	(−1.43)	(1.09)	(−2.00)	(−0.50)	(0.57)	(1.45)	(−1.61)	(0.89)	(−1.80)
Observations	470,927											
R^2 (within)	0.0184–0.0185											

Notes: Each column reports a separate regression of an indicator for switching occupation on Post_t, $\text{NTR}_{\text{ind}} \times \text{Post}_t$, a subgroup indicator (Group), $\text{NTR}_{\text{ind}} \times \text{Group}$, and the triple interaction $\text{NTR}_{\text{ind}} \times \text{Post}_t \times \text{Group}$. Controls and fixed effects as in prior tables; SEs clustered by industry. For Manufacturing, Group and NTR × Group are absorbed; the triple is identified. t statistics in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 9: Baseline Model: NTR Gap (Commuting Zone)

	(1) Wage Loss	**(2)** Hours Increase	**(3)** Leave Mfg.	**(4)** Switch Industry	**(5)** Switch Occupation
NTR Gap × Post-2001	0.117	0.221*	−0.137	0.267	0.136
	(1.11)	(1.66)	(−0.55)	(1.25)	(0.90)
Observations	470,927	470,927	71,059	470,776	470,927
R^2 (within)	0.0114	0.0063	0.0099	0.0157	0.0183

Notes: Dependent variables are shown in the column headers. Column (3) restricts the sample to individuals employed in manufacturing in the base year. All regressions include year dummies, industry, and commuting-zone fixed effects. Standard errors are clustered at the commuting-zone level. Controls include age and age squared; female; married; at least one child; bachelor's degree; high-school dropout; and household-level low- and high-income dummies. The main effect of the continuous treatment (CZ-level NTR Gap) is omitted due to collinearity with fixed effects. t statistics in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 10: Income Loss and NTR Gap (Commuting Zone): Heterogeneity by Subgroups

	Dropout	Bachelor	Female	Manufacturing	Young	Old	Married	Kids	Poor	Affluent	Black	White
NTR × Post	0.118	0.121	0.180	0.098	0.074	0.048	0.220	0.297**	0.137	0.100	0.151	−0.015
	(1.01)	(0.92)	(1.27)	(0.81)	(0.71)	(0.41)	(1.19)	(2.08)	(1.16)	(0.80)	(1.22)	(−0.08)
Group (=1)	0.059***	−0.059***	0.012**	–	−0.033***	0.031***	−0.029***	0.013**	−0.065***	0.086***	0.040***	−0.027***
	(7.12)	(−7.93)	(2.40)	–	(−4.51)	(4.29)	(−4.30)	(2.34)	(−8.62)	(10.02)	(3.00)	(−3.66)
NTR × Group	−0.078	0.085	0.115	–	0.017	0.076	0.119	0.107	0.227	−0.134	−0.025	0.288
	(−0.43)	(0.49)	(1.00)	–	(0.10)	(0.41)	(0.79)	(0.78)	(1.31)	(−0.70)	(−0.10)	(1.34)
NTR × Post × Group	−0.014	0.003	−0.129	0.309	0.244	0.401	−0.140	−0.397*	−0.127	0.043	−0.315	0.187
	(−0.04)	(0.01)	(−0.65)	(0.88)	(0.82)	(1.16)	(−0.57)	(−1.76)	(−0.55)	(0.15)	(−0.79)	(0.70)
Observations	470,927											
R^2 (within)	0.0114–0.0116											

Notes: Each column reports a separate regression of *Income Loss* on Post_t, $\text{NTR}_{cz} \times \text{Post}_t$, a subgroup indicator (Group), $\text{NTR}_{cz} \times \text{Group}$, and the triple interaction $\text{NTR}_{cz} \times \text{Post}_t \times \text{Group}$. Controls include age and age squared; female; married; at least one child; bachelor's degree; high-school dropout; and low- and high-income individual dummies. All regressions absorb commuting-zone, industry, and year fixed effects; standard errors are clustered by commuting zone. The main effect of NTR_{cz} is absorbed by fixed effects. For the Manufacturing subgroup, the Group effect and $\text{NTR}_{cz} \times \text{Group}$ are absorbed/omitted; the triple remains identified. SEs in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 11: Hours Increase and NTR Gap (Commuting Zone): Heterogeneity by Subgroups

	Dropout	Bachelor	Female	Manufacturing	Young	Old	Married	Kids	Poor	Affluent	Black	White
NTR × Post	0.304**	0.168	−0.042	0.184	0.256*	0.174	−0.040	0.325**	0.321***	0.181	0.197	0.424
	(2.45)	(0.97)	(−0.23)	(1.36)	(1.86)	(1.26)	(−0.22)	(2.07)	(2.81)	(1.26)	(1.41)	(1.37)
Group (=1)	−0.016*	0.028***	0.036***	–	−0.031***	−0.018**	0.013**	0.013**	0.039***	−0.000	0.005	−0.000
	(−1.93)	(4.10)	(4.13)		(−4.39)	(−2.41)	(2.00)	(2.56)	(5.32)	(−0.06)	(0.52)	(−0.01)
NTR × Group	0.283	0.071	−0.218	−0.159	−0.007	−0.214	−0.034	0.005	0.190	−0.058	−0.196	0.190
	(1.41)	(0.43)	(−1.17)	(−1.06)	(−0.04)	(−1.37)	(−0.23)	(0.04)	(0.90)	(−0.34)	(−0.88)	(0.99)
NTR × Post × Group	−0.731*	0.139	0.545**	0.105	−0.233	0.365	0.401**	−0.228	−0.453*	0.153	0.280	−0.256
	(−1.93)	(0.59)	(2.34)	(0.39)	(−0.92)	(1.37)	(2.13)	(−1.11)	(−1.73)	(0.63)	(0.66)	(−0.82)
Observations	470,927											
R^2 (within)	0.0063–0.0065											

Notes: Each column reports a separate regression of *hours increase* on Post_t, $\text{NTR}_{cz} \times \text{Post}_t$, a subgroup indicator (Group), $\text{NTR}_{cz} \times$Group, and the triple interaction $\text{NTR}_{cz} \times \text{Post}_t \times$Group. Controls include age and age squared; female; married; at least one child; bachelor's degree; high-school dropout; and low- and high-income dummies. All regressions absorb commuting-zone, industry, and year fixed effects; SEs clustered by commuting zone. The main effect of NTR_{cz} is absorbed by fixed effects. For the Manufacturing subgroup, the Group effect and $\text{NTR}_{cz} \times$Group are absorbed; the triple remains identified. t-statistics in parentheses. $^{*}\, p < 0.10$, $^{**}\, p < 0.05$, $^{***}\, p < 0.01$.

Table 12: Leave Manufacturing and NTR Gap (Commuting Zone): Heterogeneity by Subgroups

	Dropout	Bachelor	Female	Manufacturing	Young	Old	Married	Kids	Poor	Affluent	Black	White
NTR × Post	−0.043	−0.192	−0.072	−0.137	−0.244	−0.251	−0.025	0.338	−0.088	−0.007	−0.128	0.298
	(−0.16)	(−0.70)	(−0.23)	(−0.55)	(−0.96)	(−0.99)	(−0.05)	(0.97)	(−0.33)	(−0.02)	(−0.52)	(0.67)
Group (=1)	−0.045**	0.067***	−0.007	–	0.032*	−0.027**	0.010	−0.014	0.028	−0.008	0.013	0.004
	(−2.17)	(2.67)	(−0.49)		(1.92)	(−2.22)	(0.85)	(−1.20)	(0.85)	(−0.67)	(0.71)	(0.23)
NTR × Group	0.192	−0.381	0.349	–	−0.431	−0.052	−0.284	−0.102	0.082	−0.066	−0.078	0.238
	(0.51)	(−0.91)	(1.29)		(−1.47)	(−0.26)	(−1.09)	(−0.43)	(0.15)	(−0.23)	(−0.23)	(0.66)
NTR × Post × Group	−0.765	0.364	−0.193	–	0.733	0.877*	−0.169	−0.939**	−0.278	−0.476	−0.036	−0.508
	(−1.23)	(0.65)	(−0.29)		(1.05)	(1.68)	(−0.30)	(−2.14)	(−0.43)	(−0.95)	(−0.05)	(−1.13)
Observations	71,059											
R^2 (within)	0.0099–0.0101											

Notes: Each column reports a separate regression of *leave manufacturing* on Post_t, $\text{NTR}_{cz}\times\text{Post}_t$, a subgroup indicator (Group), $\text{NTR}_{cz}\times$Group, and the triple interaction $\text{NTR}_{cz}\times\text{Post}_t\times$Group. The sample is restricted to individuals employed in manufacturing in the baseline year. Controls include age and age squared; female; married; at least one child; bachelor's degree; high-school dropout; and low- and high-income dummies. All regressions absorb commuting-zone, industry, and year fixed effects; SEs clustered by commuting zone. The main effect of NTR_{cz} is absorbed by fixed effects. For the Manufacturing subgroup, the Group effect and $\text{NTR}_{cz}\times$Group are absorbed; the triple interaction remains identified. t-statistics in parentheses. $^{*}\, p < 0.10$, $^{**}\, p < 0.05$, $^{***}\, p < 0.01$.

Table 13: Switch Industry and NTR Gap (Commuting Zone): Heterogeneity by Subgroups

	Dropout	Bachelor	Female	Manufacturing	Young	Old	Married	Kids	Poor	Affluent	Black	White
NTR × Post	0.291	0.359	0.176	0.138	0.312	0.203	0.135	0.434^{**}	0.325	0.324	0.300	0.361
	(1.30)	(1.63)	(0.92)	(0.63)	(1.37)	(0.89)	(0.63)	(2.08)	(1.43)	(1.45)	(0.78)	(0.74)
Group (=1)	−0.006	-0.022^{***}	0.034^{***}	–	0.001	-0.024^{***}	0.008	-0.011^{*}	0.044^{***}	-0.026^{***}	0.027^{**}	-0.043^{***}
	(−0.71)	(−2.95)	(7.01)		(0.14)	(−3.00)	(1.30)	(−1.88)	(4.69)	(−3.42)	(2.46)	(−4.41)
NTR × Group	0.297	0.185	0.051	-1.277^{***}	−0.101	−0.041	-0.270^{*}	−0.019	0.290	−0.080	−0.069	0.154
	(1.44)	(1.03)	(0.45)	(−3.95)	(−0.59)	(−0.26)	(−1.78)	(−0.13)	(1.32)	(−0.53)	(−0.28)	(0.78)
NTR × Post × Group	−0.159	−0.342	0.186	0.251	−0.283	0.452	0.195	-0.349^{*}	−0.294	−0.214	−0.192	−0.121
	(−0.45)	(−1.41)	(0.74)	(0.63)	(−0.98)	(1.60)	(0.87)	(−1.80)	(−1.25)	(−0.99)	(−0.30)	(−0.26)
Observations	470,776											
R^2 (within)	0.0157–0.0159											

Notes: Each column reports a separate regression of *switch industry* on Post_t, $\text{NTR}_{cz} \times \text{Post}_t$, a subgroup indicator (Group), $\text{NTR}_{cz} \times \text{Group}$, and the triple interaction $\text{NTR}_{cz} \times \text{Post}_t \times \text{Group}$. Controls include age and age squared; female; married; at least one child; bachelor's degree; high-school dropout; and low- and high-income dummies. All regressions absorb commuting-zone, industry, and year fixed effects; standard errors are clustered by commuting zone. The main effect of NTR_{cz} is absorbed by fixed effects. For the Manufacturing subgroup, the Group effect and $\text{NTR}_{cz} \times \text{Group}$ are absorbed; the triple interaction remains identified. t-statistics in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 14: Switch Occupation and NTR Gap (Commuting Zone): Heterogeneity by Subgroups

	Dropout	Bachelor	Female	Manufacturing	Young	Old	Married	Kids	Poor	Affluent	Black	White
NTR × Post	0.091	0.229	0.044	−0.022	0.225	0.045	0.001	0.137	0.055	0.271	0.154	−0.179
	(0.60)	(1.28)	(0.25)	(−0.14)	(1.53)	(0.30)	(0.01)	(0.66)	(0.34)	(1.54)	(1.18)	(−0.50)
Group (=1)	−0.006	-0.048^{***}	0.058^{***}	–	-0.015^{*}	-0.019^{**}	0.001	-0.013^{**}	0.047^{***}	-0.030^{***}	0.034^{***}	−0.005
	(−0.79)	(−7.52)	(7.26)		(−1.74)	(−2.39)	(0.21)	(−2.78)	(6.25)	(−4.83)	(3.29)	(−0.47)
NTR × Group	0.176	0.087	−0.033	-0.689^{***}	0.262	-0.375^{*}	-0.265^{***}	0.058	0.116	−0.110	0.371^{*}	−0.283
	(0.92)	(0.56)	(−0.24)	(−5.45)	(1.65)	(−1.90)	(−2.85)	(0.49)	(0.60)	(−0.85)	(1.88)	(−1.44)
NTR × Post × Group	0.511	−0.328	0.179	0.526^{*}	−0.490	0.704^{**}	0.189	0.005	0.323	-0.515^{**}	−0.220	0.378
	(1.13)	(−1.23)	(0.88)	(1.93)	(−1.42)	(2.30)	(0.91)	(0.02)	(1.15)	(−2.04)	(−0.37)	(1.07)
Observations	470,927											
R^2 (within)	0.0183–0.0185											

Notes: Each column reports a separate regression of *switch occupation* on Post_t, $\text{NTR}_{cz} \times \text{Post}_t$, a subgroup indicator (Group), $\text{NTR}_{cz} \times \text{Group}$, and the triple interaction $\text{NTR}_{cz} \times \text{Post}_t \times \text{Group}$. Controls include age and age squared; female; married; at least one child; bachelor's degree; high-school dropout; and low- and high-income dummies. All regressions absorb commuting-zone, industry, and year fixed effects; standard errors are clustered by commuting zone. The main effect of NTR_{cz} is absorbed by fixed effects. For the Manufacturing subgroup, the Group effect may be absorbed by fixed effects; the $\text{NTR}_{cz} \times \text{Group}$ and the triple interaction remain identified (the former is significant and reported here). t-statistics in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Appendix Table 1: Matched vs. Unmatched Respondents by Survey Year

Survey Year	**Unmatched**	**Matched**	**Total**
1989	94,083	50,598	144,681
1990	52,120	55,346	107,466
1991	48,521	54,595	103,116
1992	47,194	53,994	101,188
1993	47,067	54,122	101,189
1994	47,633	49,552	97,185
1996	81,974	48,503	130,477
1997	34,757	48,591	83,348
1998	34,231	48,794	83,025
1999	34,277	49,251	83,528
2000	36,049	48,407	84,456
2001	111,029	58,518	169,547
2002	89,957	64,129	154,086
2003	80,210	68,419	148,629
2004	83,734	59,421	143,155
2005	85,510	64,909	150,419
2006	78,266	64,867	143,133
2007	74,439	66,910	141,349
2008	72,690	66,383	139,073
Total	**1,233,741**	**1,075,309**	**2,309,050**

Notes: Sample includes all respondents from survey years prior to 2009. Matched individuals are those observed in two consecutive ASEC surveys. To ensure consistency, respondents are excluded if reported sex or race changes across years, or if reported age in the second year does not increase by one year as expected or increases by more than three years.

Appendix Table 2: Comparison of Matched and Unmatched CPS Respondents

Variable	Unmatched Mean	Matched Mean	Difference	p-value
Age (years)	36.229	41.257	-5.029	0.000
Female	0.473	0.483	-0.010	2.93e-21
Married	0.525	0.670	-0.146	0.000
Lives with child < 18 (family)	0.452	0.484	-0.032	7.5e-209
Manufacturing	0.131	0.149	-0.018	7.5e-142
Black	0.130	0.088	0.042	0.000
White	0.792	0.859	-0.067	0.000
Bachelor's degree or more	0.247	0.274	-0.027	4.9e-202
No high school diploma	0.128	0.101	0.028	0.000
Affluent (liquid)	0.174	0.273	-0.099	0.000
Poor (liquid)	0.353	0.206	0.146	0.000

Notes: Sample includes respondents from survey years prior to 2009, ages 19 to 66, who are in the labor force and report an industry. Observations are excluded if geographic identifiers are missing, meaning respondents cannot be placed in either a county or a metropolitan statistical area (MSA). Matched individuals are those observed in two consecutive ASEC surveys. To ensure consistency, respondents are also excluded if reported sex or race changes across years, or if reported age in the second year does not increase by one year as expected or increases by more than three years. p-values are from two-sided t-tests for equality of means.

Table 15: Appendix Table 3: Income Loss (Levels) and NTR Gap (Industry): Heterogeneity by Subgroups

	Dropout	Bachelor	Female	Manufacturing	Young	Old	Married	Kids	Poor	Affluent	Black	White
NTR × Post	651.38	337.63	1176.56	16457.02***	1238.54	926.84	−2654.55**	1719.62	1585.39	781.96	1128.12	−18.87
	(0.62)	(0.35)	(0.76)	(3.89)	(1.12)	(0.88)	(−2.22)	(1.47)	(1.34)	(0.86)	(1.11)	(−0.01)
Group (=1)	−2176.93***	2291.38***	−218.35	–	1192.51***	−1781.83***	1966.35***	−1674.73***	3382.62***	−6782.88***	−1236.68***	782.52**
	(−9.05)	(8.58)	(−1.06)	–	(5.21)	(−4.65)	(12.88)	(−10.64)	(21.21)	(−16.62)	(−4.42)	(2.56)
NTR × Group	−931.60	−3565.16*	1490.85*	–	1227.54	−1984.44	−2776.60***	−292.77	1011.20	−2701.28*	1919.88*	−1658.17*
	(−0.86)	(−1.95)	(1.80)	–	(1.40)	(−1.12)	(−4.02)	(−0.33)	(1.29)	(−1.65)	(1.75)	(−1.73)
NTR × Post × Group	3132.99**	4310.81	−281.24	−13350.03***	−1133.01	1478.73	5265.17***	−1179.90	−2042.42	1294.65	91.48	1314.40
	(2.15)	(1.20)	(−0.14)	(−2.79)	(−0.44)	(0.47)	(3.05)	(−0.74)	(−1.27)	(0.55)	(0.03)	(0.56)
Observations						470,819						
R^2 (within)						0.0120						

Notes: Each column reports a separate regression of income loss in levels on Post_t, $\text{NTR}_{\text{ind}}\times\text{Post}_t$, a subgroup indicator (Group), $\text{NTR}_{\text{ind}}\times\text{Group}$, and the triple interaction $\text{NTR}_{\text{ind}}\times\text{Post}_t\times\text{Group}$. Controls include age and age squared; female; married; at least one child; bachelor's degree; high-school dropout; and low- and high-income dummies. All regressions absorb commuting-zone, industry, and year fixed effects; SEs clustered by industry. For the Manufacturing subgroup, the level Group effect and NTR × Group are absorbed; the triple remains identified. t statistics in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 16: Appendix Table 4: Change in Log Income and NTR Gap (Industry): Heterogeneity by Subgroups

	Dropout	Bachelor	Female	Manufacturing	Young	Old	Married	Kids	Poor	Affluent	Black	White
NTR × Post	0.063***	0.050**	0.046*	0.115	0.065***	0.078***	−0.009	0.054**	0.076***	0.064***	0.072***	−0.001
	(2.94)	(2.11)	(1.92)	(0.37)	(3.45)	(3.54)	(−0.23)	(2.05)	(3.74)	(2.95)	(3.94)	(−0.03)
Group (=1)	−0.053***	0.059***	0.012*	–	0.048***	−0.086***	0.045***	−0.032***	0.216***	−0.158***	−0.037***	−0.004
	(−6.86)	(7.13)	(1.93)	–	(6.31)	(−7.12)	(10.22)	(−5.12)	(24.59)	(−27.18)	(−3.97)	(−0.49)
NTR × Group	−0.032	0.011	−0.051	–	−0.090**	0.069*	0.012	−0.043	−0.078*	0.065***	−0.033	0.002
	(−0.87)	(0.31)	(−1.63)	–	(−2.12)	(1.72)	(0.42)	(−1.45)	(−1.94)	(2.94)	(−1.03)	(0.06)
NTR × Post × Group	0.072	0.074	0.032	−0.101	−0.033	−0.089	0.104**	0.031	−0.029	0.016	−0.061	0.082*
	(1.35)	(1.48)	(0.62)	(−0.32)	(−0.52)	(−1.36)	(2.19)	(0.76)	(−0.47)	(0.51)	(−0.75)	(1.80)
Observations	425,861											
R^2 (within)	0.020–0.021 across specs											

Notes: Each column reports a separate regression of the *change in log income* on Post_t, $\text{NTR}_{\text{ind}} \times \text{Post}_t$, a subgroup indicator (Group), $\text{NTR}_{\text{ind}} \times \text{Group}$, and the triple interaction $\text{NTR}_{\text{ind}} \times \text{Post}_t \times \text{Group}$. Controls include age and age squared; female; married; at least one child; bachelor's degree; high-school dropout; and low- and high-income dummies. All regressions absorb commuting-zone, industry, and year fixed effects; SEs clustered by industry. For the Manufacturing subgroup, the Group level and NTR×Group are absorbed; the triple remains identified. t statistics in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.