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

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Abstract

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This paper attempts to see if there are differences in these effects between demographic groups in the US case in the context of the most studied example, commonly referred to as the 'China Shock.' We examine the 'matched CPS,' which allows us to observe year-to-year economic transitions of a sample of US workers, to see if the losses in labor income fall more heavily on identifiable demographic groups.

We find that income losses are more likely in the face of a trade shock for workers in manufacturing; workers with children, workers with a bachelor's degree, and workers with high household income. By contrast, losses are *smaller* or zero for young workers or workers with low family income. We argue that the family-income findings may be due to liquidity constraints, causing low-income workers to scramble to keep their incomes from falling below the level required to meet essential expenses, and high-income workers to be more passive. These effects seem to be new to the trade literature.

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Numerous researchers have documented wage losses in local labor markets hit by rising import competition. In a wide variety of settings, labor incomes in locations dependent on import-competing industries fall relative to incomes in other locations.

This paper attempts to see if there are differences in these effects between demographic groups in the US case in the context of the most studied example, commonly referred to as the 'China Shock.' We examine the 'matched CPS,' which allows us to observed year-to-year economic transitions of a sample of US workers, to see if the losses in labor income 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 for workers in manufacturing, for workers with a bachelor's degree, and for workers with high household income. By contrast, losses are *smaller* or zero for young workers and workers with low family income. We argue that the findings on family income may be due to liquidity constraints, causing workers to scramble to keep their incomes from falling below the level required to meet essential expenses. These effects seem to be new to the trade literature.

To interpret these results, consider first 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. One possible example would be married workers. 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 was 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 consistent with some of the findings; we see some evidence that adjustment costs are higher for workers with children and lower for young workers. However, we also find that workers from high-income households and workers with a bachelor's degree are the ones most likely to see a drop in income in the face of a trade shock. Low-income workers show no tendency for a drop in income in the face of a trade shock. These findings are very difficult to rationalize with the neo-classical adjustment paradigm.

These findings can be rationalized by a consideration of liquidity constraints, an issue absent from the standard neo-classical adjustment model described above. 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 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 later 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 workers over time. Autor, Dorn, Hanson, and Song (2014) use Social Security administrative data to trace the effects on individual workers over several years. Keller and Utar (2022) do the same with Danish administrative data; Devlin, Kovak, and Morrow (2022) do something similar with Canadian data; and Pierce, Schott, and Tello-Trillo (2024) pioneer the use of employee-employer LEHD data to follow US workers. We also follow individual workers, although we are able to follow workers only through a single year of transition.

A flurry of recent work has examined differences in adjustment for workers in different demographic groups, across gender and racial lines, for example. 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. Hottman and Monarch (2024) study the effects of the China Shock on consumer prices for different US demographic groups, finding that Black workers benefitted proportionally less from lower consumer prices than other groups. Kahn, Oldenski, and Park (2023) show that the China Shock seems to have trimmed Black-White wage differentials in the US somewhat, with the opposite effect for Hispanic-White differentials. Batistich and Bond (2023) show that the earlier 'Japan Shock' appears to have blunted Black wage growth in the 1970's. Kamal, Sundaram, and Tello-Trillo (2024) show that women in firms subject to the Family Leave Act were more likely to layoff women workers and less likely to promote them, in face of the China Shock. Pierce, Schott and Tello-Trillo (2024) follow US 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.

We contribute here by examining how transitions to the China Shock for individual 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; and we show that some of the patterns are difficult to explain without recourse to liquidity constraints, which have not been considered in the literature.

2 Data.

Our sample of U.S. workers spans from 1989 to 2007 isolating the impact of China's trade shock before the financial crisis. The sample is collected from the matched Current Population Survey (CPS) March Annual Social Economic Supplement (ASEC) (Flood et al. (2021)). The supplemental survey provides more detailed income statistics than the regular

CPS questionnaires. Each respondent is surveyed over four months in one year, and then a second time during the same four months of the following year. We use the Madrian and Lefgren (2000) algorithm to match first-year data of a respondent to that respondent's second-year data, creating a mini-panel in which each worker is observed for two years. Approximately half of the respondents can be matched in this way. The survey also provides general demographics, such as sex, age, education, marital status, number of children, and ethnicity. The respondents are asked about their employment, including whether an individual participated in the labor force the previous week. Our sample is limited to those in labor force between the ages of 18 to 65, accounting for approximately 300,700 people. Each individual is classified according to their industry and occupation. Of those that can be matched, 25 percent changed occupations while 18 percent changed industries. To identify the impact of the shock on manufacturing jobs, we classified manufacturers according to the CPS industry code.

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 data 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.[1] Our sample did not have respondents from all FIPS codes, and as a result our matched CPS data includes 227 commuting zones.

Real wages and real household incomes are recorded, and CPI adjusted to 1999 dollars. We calculate the median household income by commuting zones. To classify households as poor or affluent, we compute household per-capita income using household equivalence scales following the procedure of the US Census Bureau.[2] This allows us to identify the effective size of the household, taking into account the different consumption levels of different members. A household is then classified as poor if its effective per-capita household income is less than half that of the commuting-zone median, and affluent if it is more than twice the median.

Our measure of the trade shock for the worker's commuting zone is based on the NTR gap devised by Pierce and Schott's (2016), which they and subsequent authors have shown to be a very 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

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

[2] The details are laid out at:
https://www.census.gov/topics/income-poverty/income-inequality/about/metrics/equivalence.html

to the World Trade Organization (WTO) in 2001 further ensured this status.[3] The NTR gap is defined according to Pierce and Schott (2016) as the difference between the non-NTR tariff rate and NTR rate for Chinese imports at the eight-digit Harmonized Tariff Schedule (HTS) code. It measures the degree to which different industries were hit by the elimination of the possibility of tariff increases. We created a crosswalk to map six digit HTS level industries to the CPS industry classification code and converted these tariffs to the CPS industry classification codes. Our industry codes follow Autor and Dorn's (2019) classification.

The industry level NTR gap is expressed by the following:

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

where s is the industry and h is the eight-digit Harmonized Tariff Schedule (HTS) code. The NTR gap measures the degree to which different industries were hit by the elimination of the possibility of tariff increases. It is the difference between the non-NTR tariff rate and NTR rate for Chinese imports at the eight-digit Harmonized Tariff Schedule (HTS) code in 1999. The tariff gap ranges from a decline of 20 percentage points (suitcases) to and increase of 484 percentage points (tobacco wastes). On average, the NTR gap is 28 percentage points. We first aggregate to the six-digit HTS code using the simple average. We then convert these tariffs to the Census' industry classification codes. We calculate the average NTR gap by 1987 Standard Industrial Classification (SIC) code and map the SIC codes to Census industries using the crosswalk by Autor and Dorn (2019). After aggregating to the industry level, the average NTR gap is 27 percentage points, however, the NTR gap now ranges from 0 (coal mining as well as newspaper publishing and printing) to 63 (miscellaneous fabricated textile) percentage points.

We also create a commuting zone level NTR gap, which is expressed by the following:

$$NTRgap_c = \sum_s \frac{emp_{c,s}}{emp_c} NTRgap_s \tag{2}$$

where s is the industry and c is the 1990 commuting zone. It weighs industry's NTR gap by the share of employment in tradable industries by commuting zones. The employment shares are also from 1999. National employment data are reported by the Census' County Business Patterns (CBP) data.[4] The average commuting-zone-level NTR gap is 5 percentage

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

[4] The employment data are reported by the North American Industry Classification System (NAICS). We use a crosswalk by Autor and Dorn (2016) to map the employment data to the Census' industry codes

points and the maximum gap is 22 percentage points.

For each worker, we use two measures of this trade shock. For each worker, the *industry* shock is simply the NTR gap for that worker's industry of employment. The *commuting-zone* measure of the shock is the weighted average of each industry's NTR gap, weighted by the year-2000 share of employment in tradable industries in that commuting zone.

National employment data are reported by the Census' 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' concordance. We then expanded the Autor and Dorn (2016) crosswalk to map the employment data to the Census' industry codes.

3 Empirical specification and results.

To estimate the effect of the 'China Shock' on domestic worker's income and hours worked, we estimate two difference-in-differences regression using the NTR gap as the treatment variable.

We first focus on the impact of the trade shock on a worker's income. The total labor income for the previous year is deflated by the 1999 Consumer Price Index. If a worker's stated previous year's real income is lower in the second year of interviews than the first, we say the the worker's income has declined. We follow up with analogous regressions where the dependent variable is a dummy for an increase in hours worked between the two years. Table 2 reports the summary statistics for the dependent variables by each subsample. Approximately 40 percent of individuals experienced a total income loss, 33 percent experienced a lower hourly wage, and 20 percent experienced an increase in hours. Low-income households did not experience a drop in income or wages as often as high-income household.

The baseline model estimates the effect of the trade shock on income loss using the following regression:

$$IncomeLoss_{i,s,c,t} = \alpha_{+} \beta NTRgap_s \times Post2001 + X_i \Gamma + \delta_t + \lambda_s + \gamma_c + \varepsilon_{i,s,c,t}$$

$IncomeLoss_{i,s,c,t}$ is an indicator variable if a worker's income declined, where i is the individual, s is the sector, c is the commuting zone, and t is the year. The approach taken here is simply to regress the dummy variable for income decline on the trade shock, often interacted with personal characteristics to allow for a heterogenous response. Γ is a vector of controls.[5] Year, sector, and commuting-zone fixed effects are denoted as δ_t, λ_s, and γ_c respectively. Standard errors are clustered at the industry and commuting-zone level.

We focus on four different dependent variables, which measure different aspects of a worker's response to a shock. The first is a dummy for a decline in the worker's real income between the two years. We focus on each worker's estimated total labor income for the previous year, deflated by the Consumer Price Index. If a worker's stated previous year's real income is lower in the second year of interviews than the first, we say the the worker's income has declined. The second is a dummy for an increase in hours worked, which takes a value of 1 if the worker's total estimated work hours in the second year exceed that for the first year. The third focusses on the estimated hourly wage, which is the total real labor income for the year divided by the total hours worked for the year. The dependent variable in this case takes a value of 1 if this estimated hourly wage is lower in the second year than the first year and 0 otherwise. The last dependent variable identifies workers who left manufacturing in the period observed; it takes a value of 1 if the worker was in a manufacturing industry in the first year and in a non-manufacturing industry in the second year, and 0 otherwise.

All regressions feature year, industry, and commuting-zone fixed effects, and standard errors are clustered at the commuting-zone level. They also include worker controls: age and age squared; gender; a dummy for married workers; a dummy for workers with at least one child; a dummy for a bachelor's degree and another for high-school dropouts; dummies for workers from low- and high-income households, and the average educational level of other household members of age 18 or older.

Tables 3 through 7 show the results of regressing these dependent variables on the commuting-zone shock and the worker controls just mentioned. Table 3 includes the shock and the worker controls alone; these regressions can reveal whether or not workers in general show a tendency for year-on-year adjustments when they are living in an commuting zone that is hit with an import shock. Tables 4 through 7 include interactions between the shock and the worker controls, first one interaction at a time (columns (1) through (12)) and then all together (column (13)) in order to look for heterogeneous effects for different demographic groups. Tables 8 through 12 then repeat the exercise for the industry shock.

The four columns of Table 3 correspond to the four dependent variables, income loss; hours gain; decrease in hourly wage; and leaving manufacturing. The estimates show a

[5] The controls are age, age squared, female, married, kids, manufacturing, black, white, bachelor, drop out, low-income, and high-income.

tendency for an increase in hours and for exit from manufacture in the presence of the trade shock. But the story of interest is heterogeneous response, which comes from the interactions in the following tables.

We next look in Table 4 for heterogeneous correlation between the trade shock and income losses by adding interaction terms between the trade shock and worker characteristics. Each column (1) through (12) adds to the regression the interaction of the trade shock with one of the worker characteristics in the list of controls. The minor exception is columns (5) and (6), which for convenience of interpretation feature the dummies 'young,' for workers under the age of 30, and 'old,' for workers over the age of 55, in place of age and age squared. The final column features all interactions together.

Columns (2) and (13) show a strong positive interaction for the dummy indicating a bachelor's degree.[6] Columns (7) and (8), together with (13), show a negative interaction with marriage and a positive one for children in the household, respectively. Columns (9) and (10), together with (13), show respectively, a negative interaction with the 'poor' dummy and a positive interaction with 'rich.' Surprisingly, workers with a bachelor's degree and from a high-income household, *ceteris paribus*, are more likely than other workers in the same location to report a decline in income in the face of a trade shock, and workers from low-income households are significantly *less* likely to see an income decline in the face of a trade shock. The other interactions are either insignificant or significant only in isolation.

Consideration of the standard neo-classical model sketched in the introduction would suggest that married workers, workers with children, and minority workers would be more likely to suffer income declines in the face of a trade shock, if those groups face higher switching costs. But this does not appear to be the case. The exception is Column (7), which does show an increased tendency for workers with children to see an income decline in a trade shock. Aside from that, the strong results are for workers with a college degree and workers from an affluent family to be more likely than others to see an income decline with the trade shock, and workers from a poor family to be less likely.

Table 5 follows the same structure with an increase in hours worked as the dependent variable. The main result is that workers with no high-school diploma, women workers, manufacturing workers, older workers, and Black workers are all more likely to see a decline in hours in the face of a shock, while affluent workers and workers with children are more likely to see an increase in hours.

Table 6 treats our measure of hourly wages as the dependent variable rather than labor earnings for the year, and finds broadly the same pattern as Table 4 The last table in this

[6]This is similar to a finding in Pierce, Schott, and Tello-Trillo (2024), Figure 6.

group is Table 7, where the dependent variable is a dummy for leaving manufacturing. The only variable significant both alone and with the others is the dummy for younger workers, who are somewhat less likely to leave manufacturing than others in the face of the shock.

Tables 9 through 12 fulfill the same function as Tables 4 through 7, but the measure of the shock is the industry shock rather than the commuting-zone-level shock. The overall patterns for the first three dependent variables are similar, with the exception of women workers, who show up as more likely to see a drop in income, hours worked, and the hourly wage when faced with a shock to their industry. The results of Table 12 are stronger in several ways than the previous results with the commuting-zone shock. College-educated workers, women workers, young and old workers, poor, affluent, and Black workers are all more likely to leave manufacturing in face of an industry trade shock, including in column (13), while workers with children and married workers are both less likely to do so. The effect for workers from a poor family is more than four times the size of the effect for workers from an affluent family.

Summarizing the information in these tables, in the face of the trade shock: (i) Manufacturing workers are the most likely to see a loss in income, which is not surprising because the shock was primarily an increase in imports of manufactures from China. (ii) Young workers showed a great tendency to leave manufacturing, but not much tendency to see a drop in income or hourly wage. (iii) Workers with children have a smaller tendency to leave manufacturing and a great tendency to see a reduction in income and wages. (iv) Workers whose family is poor have a strong tendency to leave manufacturing and a much *lower* tendency to lose income or see a drop in wages. Workers whose family is affluent have a weak (but positive) tendency to leave manufacturing, and a much *stronger* tendency to lose income or see a drop in wages. In fact, the negative coefficient on the interaction of the shock and the 'poor' dummy in column (13) of Tables 4, 6, 9, and 11 is the most negative of all interactions (excepting the married dummy in Table 4).

From these results, (ii) and (iii) are broadly consistent with the 'neoclassical adjustment paradigm' described in the Introduction. Finding (ii) could result from younger workers having accumulated less industry-specific human capital and also having a longer future time horizon to benefit from a switch out of a declining industry, features that are important in Dix-Carneiro (2014). This could be why younger workers are more likely to switch out of manufacturing when it is hit with a negative shock, and less likely than other workers to endure an income loss. Finding (iii) could result from higher switching costs for workers with children. This might be because children impose constraints on a caregiver's time and restrict the number of jobs that are feasible to accept, or because switching jobs may require moving geographically, which can be emotionally costly for a child. The result could be that a worker with children is less likely to leave manufacturing when it is hit with a negative shock, and is more likely to endure the income reduction that results.

On the other hand, result (iv) is of a quite different character. It is difficult to think of a reason that workers from high-income families would have systematically higher adjustment costs than those without, or that workers from low-income families would have lower adjustment costs. Note that in these regressions, we control for bachelor's degree, a high-school dropout dummy, and their interactions with the trade shock. That means that these effects are *not* simply the effect of white-collar occupations. It would be understandable if occupations that require a high level of specialized, formal education imply high industry switching costs, although some attempts to measure differences in switching costs between college- and non-college-educated workers have found little or no difference (for example, Artuç, Chaudhuri, and McLaren (2010) and Artuç and Chaudhuri, and McLaren (2015)). But if that were driving these results, the coefficient on the interaction with 'poor' and 'affluent' would disappear when controlling for the interactions with educational attainment. Comparing columns (9) and (10) with (13) in Tables 4, 6, 9, and 11, we see that including the interactions with educational attainment not only does not eliminate the family-income interactions but as often as not increases their magnitudes.

These findings together suggest an interpretation quite different from the neo-classical adjustment pardigm. A possible interpretation is that for some workers, liquidity constraints are important, and that these constraints tend to lead constrained workers to resist income declines by increasing labor supply, relative to unconstrained workers. To illustrate how liquidity constraints may have this sort of effect, we turn to a simple theoretical model.

4 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 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.[7]

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. 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 was costless to do so. Workers discount 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.

[7] It will become clear that this is not really material to the main questions of labor-supply response which will be addressed here.

4.1 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

$$u(c_1) - v(L_1) + \beta E_{\{\epsilon^T \epsilon^{NT}\}}[\left(u(c_2^T) - v(L_2^T) + \epsilon^T\right) X(w_2^T, w_2^{NT}, \epsilon^T, \epsilon^{NT}) \\ + \left(u(c_2^{NT}) - v(L_2^{NT}) + \epsilon^{NT} - \kappa\right)\left(1 - X(w_2^T, w_2^{NT}, \epsilon^T, \epsilon^{NT})\right)] \quad (3)$$

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:

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

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. 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 with the falling wage, 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, the probability of switching out of the traded sector is decreasing in A_1 and A_2 and the probability of a drop in labor income in Period 2 is increasing in A_1 and A_2 ceteris paribus.*

Proof. The first order condition with respect to $\bar{\mu}$ collapses to:

$$\bar{\mu} + \kappa = \lambda \left[w_2^{NT} L_2^{NT} - w_2^T L_2^T \right] > 0, \tag{4}$$

where λ is the multiplier in the Lagangian on the intertemporal budget constraint. The positive sign is assured by $w_2^{NT} > w_2^T$ and the finding in Proposition 1 that the labor supply is increasing in the wage in each state. It is easy to confirm that the concavity of the problem ensures that λ is decreasing in A_1 and A_2. Therefore, $\bar{\mu}$ is decreasing in A_1 and A_2, and so is the probability of a switch out of the traded sector. Q.E.D.

Summary. Putting these propositions together, in the full risk sharing version of the model, a wealthy worker will ignore the trade shock in deciding whether to switch sectors or not, and labor supply and income will fall if she does not switch; but a poor worker will be much more likely to switch as a result of a trade shock and to avoid the consequent drop in income.

4.2 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:

$$\frac{w_2^j h}{w_2^j h L_2^j - R} - dL_2^j = 0. \tag{5}$$

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 (5) and solving for $\frac{\partial L_2^j}{\partial w_2^j}$ yields:

$$\frac{\partial L_2^j}{\partial w_2^j} = -\frac{hR}{\left(w_2^j h\right)^2 + d\left(c_2^j\right)^2} < 0. \tag{6}$$

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 would *increase* the Period-2 labor supply. The reason is that the reduced wage requires 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 (6), 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.

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 (6) 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 (6) 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 labor supply in Period 1.*

Summary. In other words, in this case with a poor worker, labor income does not fall in Period 2 because the worker always does whatever needs to be done to meet essential payments and no more. This causes a great deal of disutility from excess levels of labor supply, and so in Period 2 the choice of sector is driven entirely by the need to minimize labor effort, and that means choosing the highest-wage sector. If the non-traded wage in Period 2 is higher in real terms than the traded wage in Period 1, that means that Period-2 labor supply will be lower than Period-1 labor supply.

4.3 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:

$$c_1 + \frac{c_2^j}{1+r} + R + \frac{R}{1+r} = A_1 + w_1^T h L_1^T + \frac{w_2^j h L_2^j}{1+r}. \tag{7}$$

The worker works and consumes in Period 1, resulting in savings equal to $s = A_1 + w_1^T h L_1 - R - c_1$ and beginning-of-Period-2 financial resources equal to $A_2 \equiv (1+r)s = (1+r)(A_1 + w_1^T h L_1 - R - c_1)$. 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 (3) subject to the two constraints (7). The first-order constraints yield:

$$\frac{v'(L_1^T)}{w_1^T} = \beta(1+r)E_\epsilon\left[\frac{v'(L_2^j)}{w_2^j}\right]. \tag{8}$$

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 $w_2^j < w_1^T$ is assumed 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_2. The Period-2 labor supply will maximize $u(A_2 + w_2^j h L_2^j - R) - v(L_2^j)$. Rearranging the total derivative of the first-order condition yields:

$$\frac{\partial L_2^j}{\partial w_2^j} = \frac{h(A_2 - R)}{\left(w_2^j h\right)^2 + d\left(c_2^j\right)^2}. \tag{9}$$

Period-2 labor supply is increasing in the wage if $A_2 > R$ 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, and otherwise the income effect dominates so that labor supply is downward-sloping. (If $A_2 = R$, labor supply is $L_2^j = d^{-1/2}$ regardless of the wage.) Of course, the value A_2 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 (6) 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 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, 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 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.

4.4 Comparison of the three cases.

How a worker responds to a trade shock is very much affected by her access to consumption-smoothing and risk-sharing instruments. In the event of good access to financial instruments as in Section 4.1, labor supply falls as the wage declines, and consumption smoothing is achieved through intertemporal trade. This is efficient because it allocates the high labor effort to states where the return is high. By contrast, in the absence of any financial instruments as in Section 4.2, labor supply cannot fall as the wage does because that would result in a catastrophic decline in consumption. In fact, labor supply typically *rises* in such a situation, and more so for more constrained households with less room for discretionary consumption. The intermediate case in which the worker has access to borrowing and saving but not risk sharing, as in Section 4.3, offers ambiguous outcomes, and it is easy to find cases in which a worker would respond to a particularly bad outcome by working more hours than before. But if the worker has sufficient financial reserves or high enough human capital, she can smooth her consumption across time and states and allocate labor effort to high-wage states just as in the case with full financial markets.

Propositions 2 and 4 can help interpret the results of the regressions. If a worker is poor in the situation of liquidity constraints with positive spending requirements, the worker must scramble to meet expenses in every period. This results in a high probability of switching out of a contracting sector, even if the non-pecuniary personal costs of doing so are great. The worker may well find herself in a better-paying job that will require less labor supply than before, which she would not have found had the circumstances not been so dire. That can explain the interaction coefficients with the 'poor' dummy in Tables 9, 10, 11, and 12. Meanwhile, an affluent worker is less likely to incur the non-pecuniary cost of switching sectors in response to the shock, and thus more likely to stay in the contracting sector and incur a wage loss and an income loss. In the case of liquidity constraints, that would also imply an increase in labor supply. These results can help interpret the coefficients on the interaction with the 'affluent' dummy in the same series of tables.

5 Conclusions.

We have examined how workers adjust to trade shocks in US labor markets, using the matched CPS. We find some results that fit neatly with the neo-classical adjustment paradigm: Young workers are more mobile in response to the shock, changing industry readily and avoiding income losses. Workers with children have the opposite experience, having less-than-average tendency to switch out of the sector that receives the shock, and a higher-than-average tendency to suffer income losses. Both of these findings are consistent with differential adjustment shocks for those groups compared to the average.

On the other hand, some findings are hard to reconcile with that overall approach. Workers from families with low per-capita income tend to be extremely mobile in response to the shock, avoiding wage and income losses more than other classes of worker, while workers from an affluent family are more passive, switching less frequently than other workers, incurring income losses more often. We argue that a model with individual liquidity constraints can help understand these findings. Existing work on labor adjustment to trade shocks has not taken liquidity constraints into account, but these results suggest that they may be an important feature of the problem for many households.

6 Appendix.

Proof of Proposition 2. 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 (6) is less than unity in absolute value. That elasticity can be written as:

$$\frac{w_2^j}{L_2^j}\frac{\partial L_2^j}{\partial w_2^j} = -\frac{w_2^j hR/L_2^j}{\left(w_2^j h\right)^2 + d\left(c_2^j\right)^2} > -\frac{w_2^j hR/L_2^j}{\left(w_2^j h\right)^2} = -\frac{R}{w_2^j hL_2^j} > -1. \tag{10}$$

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

Proof of Proposition 3.

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:

$$whu'(c) = v'(L), \text{ or } \frac{wh}{A + whL - R} - dL = 0, \tag{11}$$

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:

$$\frac{\partial L^*}{\partial w} = \frac{h(A - R)}{(wh)^2 + d\,(c)^2} \tag{12}$$

$$\frac{\partial L^*}{\partial h} = \frac{w(A - R)}{(wh)^2 + d\,(c)^2} \tag{13}$$

$$\frac{\partial L^*}{\partial A} = \frac{-wh}{(wh)^2 + d\,(c)^2} < 0. \tag{14}$$

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:

$$\frac{\partial c^*}{\partial A} = \frac{d\,(c)^2}{(wh)^2 + d\,(c)^2} \in (0, 1). \tag{15}$$

The Envelope Theorem ensures that:

$$\frac{\partial V}{\partial A} = u'(c^*) = \frac{1}{c^*} = \frac{1}{A + whL^* - R} > 0. \tag{16}$$

Condition (15), then, ensures that $\frac{\partial^2 V}{\partial A^2} < 0$.

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

$$\max_s \left(V(A_1 - s, w_1^T, h, R) + \beta E_\epsilon \max_j \{V((1+r)s, w_2^j, h, R) + \epsilon^j\} \right), \tag{17}$$

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

$$u'(c_1) = \beta(1+r)E_j u'(c_2^j), \tag{18}$$

or in other words,

$$\frac{1}{A_1 - s + w_1^T h L_1^T - R} = \beta(1+r)E_j \left[\frac{1}{(1+r)s + w_2^j h L_2^j - R} \right], \tag{19}$$

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:

$$\rho(A_2, \nu) = \frac{\exp(V(A_2, w_2^{NT}, h, R)/\nu)}{\exp(V(A_2, w_2^{NT}, h, R)/\nu) + \exp(V(A_2, w_2^T, h, R)/\nu)} \tag{20}$$

$$= \frac{1}{1 + \exp((V(A_2, w_2^T, h, R) - V(A_2, w_2^{NT}, h, R))/\nu)}, \tag{21}$$

written as a function of $A_2 = (1+r)s$, 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 $A_2 \geq R$, then $L_2^j < L_1^T$ for $j = T, NT$.

Proof. Suppose that $A_2 \geq R$. Since $w_2^{NT} > w_2^T$, consumption is greater in Period 2 in the NT sector than in the T sector. (By (12), 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 (11), $\frac{v'(L_2^{NT})}{w_2^{NT}} < \frac{v'(L_2^T)}{w_2^T}$. By (8), 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 (12), $L_2^T < L_2^{NT}$, 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 $(1+r)s = A_2 > R$. 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 (6) 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 (11) shows that $L(n) \to 0$. Now, the second-period outcomes can be studied with (6), where A takes the value $(1+r)s(n) \leq R$ for all n. If $A = R$, (11) 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 (8) will fail.

This establishes the claim that for A_1 large enough $A_2 > R$. 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, (11) 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 (18) will fail.

Therefore, for large enough h, we will have $A_2 > R$ and $L_1^T > L_2^j$ for $j = T, NT$. This establishes Claim (iii). *QED.*

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Table 1: Summary Statistics Controls

	count	mean	sd	min	max
AGE	302708	40.77756	11.60667	18	65
age_2	302708	1797.524	958.6091	324	4225
female	302708	.4783719	.4995328	0	1
married	302708	.6466231	.4780193	0	1
kids	302708	.4595022	.4983581	0	1
manufacturing	302708	.152553	.3595566	0	1
black	302708	.0986132	.2981424	0	1
white	302708	.8468954	.3600889	0	1
bachelor	302708	.2866492	.452197	0	1
drop_out	295313	.0901586	.2864093	0	1
poor_pc_hh	302708	.1012494	.3016592	0	1
median_pc_hh	302708	.6980522	.4591035	0	1
affluent_pc_hh	302708	.2006984	.4005235	0	1

N: Number of observations, SD: Standard deviation, Min: Minimum value, Max: Maximum value

Table 2: Summary Statistics Dependent Variables

Full Sample			
	count	mean	sd
income loss	302708	.3988365	.4896598
hour_increase	302708	.1981051	.3985724
hourly_loss	302708	.3322674	.4710271
leave_man	302708	.0356614	.1854449
Low-Income			
	count	mean	sd
income loss	30649	.2736468	.4458371
hour_increase	30649	.2280335	.4195712
hourly_loss	30649	.2708082	.4443845
leave_man	30649	.0431662	.2032344
Medium-Income			
	count	mean	sd
income loss	211306	.3919198	.4881801
hour_increase	211306	.190889	.3930027
hourly_loss	211306	.3243069	.4681164
leave_man	211306	.0347789	.1832199
High-Income			
	count	mean	sd
income loss	60753	.4860501	.4998095
hour_increase	60753	.2081049	.4059557
hourly_loss	60753	.3909601	.4879695
leave_man	60753	.0349448	.1836415

Table 3: Baseline Model NTR Gap Commuting Zone

	(1)	(2)	(3)	(4)
NTR_post2001	0.153	0.228***	0.0846	0.157***
	(1.61)	(2.93)	(0.93)	(4.80)
Observations	295,313	295,313	295,313	295,313
R^2	0.027	0.065	0.108	0.225

t statistics in parentheses

All regressions include year, commuting zone, and industry fixed effects with robust standard errors. The regressions include the following controls: age and age squared; gender; a dummy for married workers; a dummy for workers with at least one child; a dummy for a bachelor's degree and another for high-school dropouts; and dummies for workers from low- and high-income household. Each column corresponds to a different dependent variable. The variables are income loss, increase in hours, hourly wage loss, and leave manufacturing, respectively.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 4: Income loss: Commuting-zone shock.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
NTR_post2001	0.154	0.0488	0.146	0.159	0.128	0.175*	0.257**	0.0899	0.177*	0.0938	0.165*	0.0202	-0.0253
	(1.61)	(0.50)	(1.44)	(1.62)	(1.34)	(1.83)	(2.36)	(0.89)	(1.85)	(0.97)	(1.73)	(0.15)	(-0.12)
Shock_drop_out	-0.00812												0.188
	(-0.06)												(1.35)
Shock_bachelor		0.381***											0.344***
		(4.66)											(3.94)
Shock_female			0.0146										0.0184
			(0.20)										(0.24)
Shock_man				-0.0217									0.0173
				(-0.22)									(0.17)
Shock_young					0.165*								0.159
					(1.69)								(1.53)
Shock_old						-0.145							-0.0349
						(-1.44)							(-0.32)
Shock_married							-0.152*						-0.269***
							(-1.93)						(-3.08)
Shock_kids								0.141*					0.266***
								(1.89)					(3.17)
Shock_poor									-0.248**				-0.253*
									(-1.98)				(-1.91)
Shock_affluent										0.286***			0.271***
										(3.12)			(2.74)
Shock_black											-0.201		-0.104
											(-1.48)		(-0.48)
Shock_white												0.147	0.0807
												(1.32)	(0.46)
Observations	295,313	295,313	295,313	295,313	295,313	295,313	295,313	295,313	295,313	295,313	295,313	295,313	295,313
R^2	0.027	0.027	0.027	0.027	0.027	0.027	0.027	0.027	0.027	0.027	0.027	0.027	0.027

Table 5: Increase in hours: Commuting-zone shock.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
NTR_post2001	0.265***	0.165**	0.287***	0.278***	0.228***	0.304***	0.202**	0.148*	0.232***	0.183**	0.255***	0.0485	0.561***
	(3.50)	(2.14)	(3.57)	(3.56)	(2.99)	(4.00)	(2.34)	(1.85)	(3.06)	(2.38)	(3.37)	(0.44)	(3.25)
Shock_drop_out	-0.408***												-0.320***
	(-3.87)												(-2.91)
Shock_bachelor		0.228***											0.108
		(3.52)											(1.57)
Shock_female			-0.122**										-0.144**
			(-2.07)										(-2.41)
Shock_man				-0.191**									-0.197**
				(-2.41)									(-2.45)
Shock_young					0.00263								-0.0644
					(0.03)								(-0.78)
Shock_old						-0.496***							-0.466***
						(-6.21)							(-5.48)
Shock_married							0.0379						-0.0515
							(0.61)						(-0.74)
Shock_kids								0.179***					0.135**
								(3.02)					(2.03)
Shock_poor									-0.0413				0.0862
									(-0.42)				(0.82)
Shock_affluent										0.218***			0.214***
										(3.01)			(2.73)
Shock_black											-0.447***		-0.609***
											(-4.14)		(-3.56)
Shock_white												0.199**	-0.192
												(2.25)	(-1.38)
Observations	295,313	295,313	295,313	295,313	295,313	295,313	295,313	295,313	295,313	295,313	295,313	295,313	295,313
R^2	0.065	0.065	0.065	0.065	0.065	0.065	0.065	0.065	0.065	0.065	0.065	0.065	0.065

Table 6: Hourly wage loss: Commuting-zone shock.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
NTR_post2001	0.0872	0.0316	0.139	0.0858	0.0817	0.0957	0.108	0.0208	0.124	-0.0400	0.0994	-0.0583	0.0343
	(0.99)	(0.35)	(1.49)	(0.95)	(0.92)	(1.08)	(1.08)	(0.22)	(1.41)	(-0.45)	(1.13)	(-0.46)	(0.17)
Shock_drop_out	-0.0286												0.154
	(-0.23)												(1.20)
Shock_bachelor		0.193**											0.0290
		(2.56)											(0.36)
Shock_female			-0.112										-0.106
			(-1.63)										(-1.52)
Shock_man				-0.00450									-0.0199
				(-0.05)									(-0.21)
Shock_young					0.0191								0.0569
					(0.21)								(0.59)
Shock_old						-0.0722							-0.00192
						(-0.78)							(-0.02)
Shock_married							-0.0347						-0.218***
							(-0.48)						(-2.71)
Shock_kids								0.142**					0.334***
								(2.07)					(4.32)
Shock_poor									-0.419***				-0.387***
									(-3.64)				(-3.17)
Shock_affluent										0.599***			0.657***
										(7.11)			(7.21)
Shock_black											-0.251**		-0.199
											(-2.00)		(-1.00)
Shock_white												0.158	-0.0143
												(1.54)	(-0.09)
Observations	295,313	295,313	295,313	295,313	295,313	295,313	295,313	295,313	295,313	295,313	295,313	295,313	295,313
R^2	0.108	0.108	0.108	0.108	0.108	0.108	0.108	0.108	0.108	0.108	0.108	0.108	0.108

Table 7: Leave Manufacturing: Commuting-zone shock.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
NTR_post2001	0.146***	0.165***	0.187***	0.0228	0.172***	0.153***	0.166***	0.169***	0.152***	0.155***	0.159***	0.151***	0.0697
	(4.51)	(4.99)	(5.43)	(0.69)	(5.30)	(4.70)	(4.48)	(4.95)	(4.70)	(4.74)	(4.94)	(3.21)	(0.95)
Shock_drop_out	0.124***												0.0763
	(2.75)												(1.62)
Shock_bachelor		-0.0273											0.00866
		(-0.98)											(0.29)
Shock_female			-0.0603**										-0.00630
			(-2.39)										(-0.25)
Shock_man				0.519***									0.514***
				(15.33)									(14.94)
Shock_young					-0.100***								-0.0917***
					(-3.01)								(-2.60)
Shock_old						0.0288							0.00512
						(0.84)							(0.14)
Shock_married							-0.0120						-0.0371
							(-0.45)						(-1.25)
Shock_kids								-0.0257					-0.0218
								(-1.01)					(-0.77)
Shock_poor									0.0543				0.0720
									(1.28)				(1.60)
Shock_affluent										0.00965			0.0139
										(0.31)			(0.42)
Shock_black											-0.0313		-0.0533
											(-0.68)		(-0.73)
Shock_white												0.00734	-0.0115
												(0.19)	(-0.19)
Observations	295,313	295,313	295,313	295,313	295,313	295,313	295,313	295,313	295,313	295,313	295,313	295,313	295,313
R^2	0.225	0.225	0.225	0.225	0.225	0.225	0.225	0.225	0.225	0.225	0.225	0.225	0.225

Table 8: Baseline Model NTR Gap Industry

	(1)	(2)	(3)	(4)
NTR_post2001	-0.00179	-0.0150	-0.00509	0.183***
	(-0.10)	(-1.09)	(-0.30)	(12.29)
Observations	295,313	295,313	295,313	295,313
R^2	0.027	0.065	0.108	0.227

t statistics in parentheses

All regressions include year, commuting zone, and industry fixed effects with robust standard errors. The regressions include the following controls: age and age squared; gender; a dummy for married workers; a dummy for workers with at least one child; a dummy for a bachelor's degree and another for high-school dropouts; and dummies for workers from low- and high-income household. Each column corresponds to a different dependent variable. The variables are income loss, increase in hours, hourly wage loss, and leave manufacturing, respectively.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 9: Income loss: Industry shock.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
NTR_post2001	-0.00544	-0.00584	0.0196	-0.536**	-0.00458	-0.00773	-0.00337	-0.0201	0.00644	-0.0151	-0.00306	0.000907	-0.559**
	(-0.30)	(-0.30)	(0.96)	(-2.09)	(-0.25)	(-0.42)	(-0.12)	(-0.93)	(0.36)	(-0.80)	(-0.17)	(0.02)	(-2.12)
Shock_drop_out	0.0285												0.0629
	(0.67)												(1.39)
Shock_bachelor		0.0143											-0.0120
		(0.46)											(-0.35)
Shock_female			-0.0618**										-0.0641**
			(-2.09)										(-2.14)
Shock_man				0.536**									0.533**
				(2.09)									(2.08)
Shock_young					0.0260								0.0432
					(0.59)								(0.93)
Shock_old						0.0414							0.0694*
						(1.05)							(1.65)
Shock_married							0.00226						-0.0287
							(0.07)						(-0.86)
Shock_kids								0.0400					0.0820***
								(1.44)					(2.59)
Shock_poor									-0.0899*				-0.107**
									(-1.85)				(-2.08)
Shock_affluent										0.0628*			0.0834**
										(1.84)			(2.22)
Shock_black											0.0197		0.0380
											(0.35)		(0.51)
Shock_white												-0.00317	0.000867
												(-0.08)	(0.02)
Observations	295,313	295,313	295,313	295,313	295,313	295,313	295,313	295,313	295,313	295,313	295,313	295,313	295,313
R^2	0.027	0.027	0.027	0.027	0.027	0.027	0.027	0.027	0.027	0.027	0.027	0.027	0.027

Table 10: Increase in hours: Industry shock.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
NTR_post2001	-0.00610	-0.0352**	0.0134	0.0934	-0.00733	-0.0172	-0.0335	-0.0183	-0.00383	-0.0356**	-0.00697	-0.0693**	0.135
	(-0.42)	(-2.26)	(0.83)	(0.46)	(-0.51)	(-1.18)	(-1.54)	(-1.07)	(-0.27)	(-2.37)	(-0.49)	(-2.30)	(0.65)
Shock_drop_out	-0.0696**												-0.0245
	(-2.05)												(-0.68)
Shock_bachelor		0.0715***											0.0272
		(2.88)											(1.00)
Shock_female			-0.0822***										-0.0741***
			(-3.51)										(-3.12)
Shock_man				-0.109									-0.125
				(-0.53)									(-0.62)
Shock_young					-0.0713**								-0.0610*
					(-2.03)								(-1.67)
Shock_old						0.0155							0.0143
						(0.50)							(0.43)
Shock_married							0.0265						-0.0197
							(1.11)						(-0.75)
Shock_kids								0.00735					0.0316
								(0.33)					(1.26)
Shock_poor									-0.122***				-0.0852**
									(-3.16)				(-2.10)
Shock_affluent										0.0972***			0.0736**
										(3.60)			(2.47)
Shock_black											-0.125***		-0.103*
											(-2.79)		(-1.74)
Shock_white												0.0637**	-0.00147
												(2.03)	(-0.04)
Observations	295,313	295,313	295,313	295,313	295,313	295,313	295,313	295,313	295,313	295,313	295,313	295,313	295,313
R^2	0.065	0.065	0.065	0.065	0.065	0.065	0.065	0.065	0.065	0.065	0.065	0.065	0.065

Table 11: Hourly wage loss: Industry shock.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
NTR_post2001	-0.000513	-0.0125	0.0262	-0.386	-0.00321	-0.0117	-0.0368	-0.0331*	0.0122	-0.0270	0.000111	-0.0570	-0.417*
	(-0.03)	(-0.69)	(1.41)	(-1.63)	(-0.19)	(-0.69)	(-1.46)	(-1.66)	(0.73)	(-1.55)	(0.01)	(-1.63)	(-1.72)
Shock_drop_out	-0.0358												0.0148
	(-0.91)												(0.36)
Shock_bachelor		0.0262											-0.0327
		(0.91)											(-1.04)
Shock_female			-0.0906***										-0.0842***
			(-3.33)										(-3.05)
Shock_man				0.382									0.367
				(1.62)									(1.55)
Shock_young					-0.0175								0.0145
					(-0.43)								(0.34)
Shock_old						0.0461							0.0767**
						(1.27)							(1.98)
Shock_married							0.0454						-0.0121
							(1.63)						(-0.39)
Shock_kids								0.0615**					0.115***
								(2.40)					(3.94)
Shock_poor									-0.188***				-0.184***
									(-4.20)				(-3.90)
Shock_affluent										0.103***			0.117***
										(3.30)			(3.37)
Shock_black											-0.0812		-0.0258
											(-1.56)		(-0.38)
Shock_white												0.0610*	0.0232
												(1.67)	(0.49)
Observations	295,313	295,313	295,313	295,313	295,313	295,313	295,313	295,313	295,313	295,313	295,313	295,313	295,313
R^2	0.108	0.108	0.108	0.108	0.108	0.108	0.108	0.108	0.108	0.108	0.108	0.108	0.108

Table 12: Leave Manufacturing: Industry shock.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
NTR_post2001	0.176***	0.171***	0.157***	-0.00840	0.156***	0.171***	0.273***	0.216***	0.158***	0.172***	0.177***	0.227***	-0.102
	(28.39)	(25.83)	(22.90)	(-0.10)	(25.38)	(27.56)	(29.42)	(29.58)	(25.92)	(26.88)	(29.26)	(17.64)	(-1.15)
Shock_drop_out	0.0521***												0.0218
	(3.60)												(1.43)
Shock_bachelor		0.0404***											0.0772***
		(3.81)											(6.68)
Shock_female			0.0744***										0.0632***
			(7.44)										(6.25)
Shock_man				0.192**									0.226***
				(2.21)									(2.60)
Shock_young					0.252***								0.239***
					(16.78)								(15.31)
Shock_old						0.0783***							0.103***
						(5.87)							(7.23)
Shock_married							-0.129***						-0.0692***
							(-12.62)						(-6.17)
Shock_kids								-0.0739***					-0.0463***
								(-7.83)					(-4.34)
Shock_poor									0.267***				0.276***
									(16.22)				(15.97)
Shock_affluent										0.0499***			0.0604***
										(4.32)			(4.76)
Shock_black											0.0910***		0.0557**
											(4.75)		(2.22)
Shock_white												-0.0519***	0.000976
												(-3.87)	(0.06)
Observations	295,313	295,313	295,313	295,313	295,313	295,313	295,313	295,313	295,313	295,313	295,313	295,313	295,313
R^2	0.227	0.227	0.227	0.227	0.228	0.227	0.227	0.227	0.228	0.227	0.227	0.227	0.229