Obsolescence Rents: Teamsters, Truckers & Impending Computerization*

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Abstract

Technological innovation, such as self-driving trucks, threatens occupations, such as truck drivers, with sudden obsolescence. Using a bare-bones overlapping generations model, we examine an occupation facing possible obsolescence. The occupation pays *'obsolescence rents,'* with fewer and older workers remaining in the occupation. We study teamsters at the dawn of the motor truck, current occupations threatened by computerization, and truckers dreading robotic trucks. As predicted, wages in threatened occupations rise, employment falls, and the occupations become 'grayer'. Older workers become more likely to enter and less likely to exit the occupation than young ones and sometimes even increase in number.

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1 Introduction

Self-driving trucks now seem all but inevitable. While their adoption will almost certainly dramatically reduce demand for truck drivers, their exact arrival date is uncertain. However, their *prospect* should also affect worker behavior even before these shocks arrive. We study labor markets where a demand shock is expected but has not yet arrived.

In the next section, we model a labor market with an impending shock where occupational choices are hard to reverse. We show that during the *anticipatory-dread stage*, the stretch of time when young workers expect that demand for an occupation may decline dramatically in their lifetime, those entering the occupation receive an *obsolescence rent.* This can be viewed as compensation for acquiring occupation-specific human capital whose usefulness is liable to plummet.

The occupation's workforce is older during the anticipatory-dread stage than either before the shock's announcement or after the dust settles. Young workers are reluctant to enter, but older workers - unlikely to be stuck holding an empty bag - are attracted by the obsolescence rent.

Wages are lowest immediately after the shock. Anticipation of the shock reduces employment; its arrival reduces it further. The aftermath of such negative labor demand shocks is well studied in seminal work such as Dorn et al. (2009), Autor et al. (2016), and Batistich and Bond (2023) that focus on shocks to the demand for occupations, and Fillmore and Hall (2021) which focuses on technological change within an occupation. Our empirical evidence adds to this aspect of the literature only in passing.

We investigate the empirical predictions of our model using one historical episode (the rise of motor trucks) and two contemporary settings where anticipatory dread is plausible (the likely arrival of self-driving trucks and the threat of computerization). We see signs that the threat of artificial intelligence is also causing anticipatory dread but it is not yet clear which workers are at risk and which may benefit.

The rise of motor trucks had become predictable by roughly 1910, but the shock did not hit until after World War I. Section 3 investigates the model's predictions by studying the market for teamsters during this period. Teamsters drove teams of horses that pulled wagons and were the antecedents of today's truck drivers.

Subject to inevitable data limitations, our results are broadly consistent with our predictions. We find that teamsters' wages rose before the shock and then plummeted. Employment fell even while wages rose and then collapsed further as wages crashed. The proportion of new teamsters who were young fell, while the proportion of exiting teamsters who were young rose. *Most significantly*, older workers became *more* likely to enter work as teamsters and *less* likely to leave. Consequently, the proportion of older workers employed as teamsters rose. These outcomes do not arise naturally in a model in which negatively shocked occupations age because young workers do not enter, but some older workers remain because they have accumulated occupation-specific human capital.

Additionally, drawing informally on Cavounidis and Lang (2020), we anticipate that once the shock hits, older affected workers will tend to shift to closely related jobs that are less adversely affected by the shock. In contrast, younger ones will be more likely to 'retrain' for ascendant jobs. Former teamsters were much more likely to take up motor truck driving if they were young.

For more contemporary dread, we turn to Frey and Osborne (2017) who in 2013, using 2010 data, estimated the probability that an occupation would be eliminated by computerization by 2030. We restrict the data to ensure that the occupation had not already been substantially shocked by 2019. We show that occupations at greater risk had slower employment and higher wage growth. These occupations aged more rapidly than those less at risk, in part due to the aging of workers who enter at-risk occupations.

Finally, section 5 briefly considers the modern trucking industry, which motivated our original investigation. We cannot establish definitively that overall employment is already declining in anticipation of automation. However, we provide decisive evidence that the occupation is aging rapidly, indicating that young workers are reluctant to become or remain truckers.

More broadly, our findings establish that an increase in an occupation's wages is sometimes not a testament to its strong demand but instead indicates that workers are pessimistic about its future. An even better indicator of worker beliefs may be the age profile of the workers it attracts. Further, our findings establish that if there is some degree of anticipation, using wages and employment to measure the size of shocks may be biased in opposite directions. The gap in employment between anticipatory dread and the aftermath is *lower* than that gap between the no-shock steady state and the aftermath. The reverse holds for wages.

Our model is related to macroeconomic models of labor supply decisions with forward-looking agents in the context of structural change. Like us, Hobijn et al. (2019) studies the effect of retraining frictions. We also use idiosyncratic preferences (or skills) for occupations like Lagakos and Waugh (2013), and our agents pick jobs taking into account current and future wages, as in Bárány and Siegel

(2018).

In studying the fates of workers of different vintages using an overlapping generations model, our model is most similar to Chari and Hopenhayn (1991). However, they analyze the steady-state dynamics of technology adoption across generations on a deterministic balanced growth path. Instead, we study a model in which a one-off technological change arrives at an uncertain time.

Like Acemoglu and Restrepo (2018), we are interested in the wage dynamics caused by technology shocks, although our shocks are fundamentally microeconomic. Finally, our paper relates to those studying how technological change affects selection into occupations, such as Ocampo (2022).

Castex et al. (2024) is closest to this paper. They develop a three-period model in which workers learn in the second period that one of two jobs may be subject to a third-period shock. Their focus is only on the worker side of the market and, in that setting, on how workers of different abilities respond to the news, while we focus on age. Like them, we rely on Frey and Osborne (2017) for part of our empirical analysis.

2 A Model of an Occupation Passing Into Obsolescence

We begin with a simple overlapping generations (OLG) model in which each individual lives and works for two periods. Initially, we assume workers choose their occupation in the first period and cannot move following a shock. Later, we allow for limited occupational mobility. We use a two-period OLG model because it allows us to distinguish young and old workers straightforwardly while remaining tractable. However, tractability comes with costs. The stark assumption that large groups of workers are born and die together makes convergence to steady-state employment and wages non-monotonic. Consequently, most of our results focus on the steady state in each stage of obsolescence rather than the dynamics.

2.1 Wages and Employment with No Mobility

We first solve a model where individuals pick a job for life. A unit measure of workers is born each period, and each worker lives for two periods. Workers choose an occupation when born, which they keep for both periods they are alive. We focus on a single occupation, which we dub 'widgeting'.

2.1.1 Setup

We take as a primitive the inverse demand or *wage function*. We denote the wage function before the shock arrives by $w_h(\cdot)$ and after it arrives by $w_l(\cdot)$. Young and old workers are equally productive perfect substitutes. Therefore, the wage is a function of the total number of workers. The shock is a negative one, so wages are lower after the shock: $w_l(x) < w_h(x)$ for all x. We assume that the wage functions are differentiable and downwards-sloping so that $w_h' < 0$ and $w_l' < 0$. For convenience, we assume that $w_h(0) \leq 1$ and that $w_l(2) \geq 0$ so that the wage always lies between 0 and 1.

We investigate three stages: the 'no-shock' (N) stage, in which workers believe the wage function will remain w_h forever; the 'anticipatory dread' (D) stage in which workers believe the wage function will transition from w_h to w_l at a constant hazard λ; and the 'aftermath' (A) stage, in which workers believe the wage function will remain w_l forever. These correspond to the three phases of obsolescence: before the risk of obsolescence is perceived, once it is on the horizon but perceived to arrive at an uncertain time, and after its arrival.

To model a continuous widgeting labor supply, we endow workers with 'preferences' for widgeting. Formally, when workers are born, they receive a random draw, ϑ, of the *per-period disutility from widgeting.* Without loss of generality, we set the wage and disutility at the outside option to 0. Thus, a worker born at t with a draw ϑ chooses to be a widgeter if

$$(w_t - \vartheta) + \delta(E[w_{t+1}] - \vartheta) > 0 \tag{1}$$

where the wage today is w_t, $\delta \in (0, 1)$ is the common discount factor, and the expected wage tomorrow is $E[w_{t+1}]$. We assume workers are risk-neutral; hence, all effects in our model operate through expected wages. Introducing risk aversion would sharpen the effect of uncertainty on labor supply.

We assume that *lifetime* widgeting disutility $(1 + \delta)\vartheta$ follows CDF F, which is continuous and strictly increasing on $[0, 1+\delta]$. Effectively, F maps the expected net present value of wages from this job to the fraction of young workers who become widgeters or, equivalently, the number of young widgeters. In other words, when the wage today is w_t and the expected wage tomorrow is $E[w_{t+1}]$, the number of young widgeters today ought to be $F(w_t + \delta E[w_{t+1}])$.

To summarize, our model posits that more young workers choose to become widgeters when they expect higher lifetime wages, that widgeter wages, in turn, decrease in the total number of workers in the occupation, and that the arrival of the shock transitions the market to a lower demand function.

2.1.2 Steady States: No Shock, Anticipation, and Post-Shock

A solution to the model is a triple of continuous functions (V_N, V_D, V_A), one for each stage, mapping the number of old widgeters today to the expected discounted lifetime earnings of a young widgeter. For instance, when there are o old widgeters in the no-shock stage, a young entrant expects to earn $V_N(o)$. Thus, the proportion (number) of young workers who become widgeters is $F\left(V_N\left(o\right)\right)$. In the next period, there will be $F(V_N(o))$ old and $F(V_N(F(V_N(o)))) = (F \circ V_N)^2(o)$ young widgeters. The new generation enters widgeting based on their expected discounted earnings given the number of old widgeters, who had, in turn, entered when young based on the previous generation of old widgeters, and so on.

Thus, recalling that wages depend on the sum of young and old widgeters, for each $o \in [0, 1]$, a solution must satisfy

$$V_N(o) = \underbrace{w_h(o + F(V_N(o)))}_{\text{wage today}} + \delta \underbrace{w_h(F(V_N(o)) + (F \circ V_N)^2(o))}_{\text{wage tomorrow}} \tag{2}$$

$$V_D(o) = \underbrace{w_h(o + F(V_D(o)))}_{\text{wage today}} + \delta[\lambda \underbrace{w_l(F(V_D(o)) + (F \circ V_A \circ F \circ V_D)(o))}_{\text{shocked wage tomorrow}} \tag{3}$$
$$+ (1 - \lambda) \underbrace{w_h(F(V_D(o)) + (F \circ V_D)^2(o))}_{\text{not-shocked wage tomorrow}}]$$

$$V_A(o) = \underbrace{w_l(o + F(V_A(o)))}_{\text{wage today}} + \delta \underbrace{w_l(F(V_A(o)) + (F \circ V_A)^2(o))}_{\text{wage tomorrow}}. \tag{4}$$

Given a solution,[1] we can define steady states in the number of old widgeters $\{o_N^*, o_A^*, o_D^*\}$ in the no shock, aftermath, and dread stages, respectively. Steady states must satisfy

$$F(V_N(o_N^*)) = \qquad F((1 + \delta)w_h(2o_N^*)) = \quad o_N^* \tag{5}$$

$$F(V_D(o_D^*)) = \quad F((1 + \delta(1 - \lambda))w_h(2o_D^*) + \delta\lambda w_l(o_D^* + F(V_A(o_D^*)))) = \quad o_D^* \tag{6}$$

$$F(V_A(o_A^*)) = \qquad F((1 + \delta)w_l(2o_A^*)) = \quad o_A^* \tag{7}$$

For a given solution, existence and uniqueness of steady states o_N^* and o_A^* is

[1] We assume a solution exists; while this is easy to verify in certain (e.g., linear) setups, deriving necessary and sufficient conditions is beyond the scope of this paper.

immediate from the fact that w is strictly decreasing, F is strictly increasing, and both are continuous. We now use this to show that the solution must be unique.

Proposition 1. *The solution* (V_N, V_A, V_D) *is unique.*

Proof. All proofs are in Appendix A. □

The intuition for the result is as follows. If there were two solutions, they would specify different wages for some number of old workers, given equilibrium entry. The solution with higher wages in the first period must specify *less* entry that period, but this is only rationalizable by a larger difference in wages the next period, in the opposite direction. That difference can, in turn, only be rationalized by an even larger wage difference the following period, and so on, with a lower bound on wage differences that grows exponentially. As wages are bounded, this leads to a contradiction.

As the solution is continuous, $F \circ V_D$ is also continuous so that the existence of an anticipatory-dread steady state o_D^* follows from Brouwer. Showing that o_D^* is also unique takes a bit of work.

Proposition 2. $F(V_D(\cdot))$ *has a unique steady state* o_D^*.

2.1.3 Wages and Employment in the Three Steady States

The uniqueness of the three steady states allows us to rank their wages and employment levels. The following proposition encompasses two facts. First, widgeter employment is highest in the no-shock steady state, followed by the anticipatory-dread steady state, which in turn features more widgeters than the aftermath steady state. Second, wages in the anticipatory-dread steady state are higher than wages in the no-shock steady state, which are, in turn, higher than wages in the aftermath steady state.

Proposition 3. *The steady-state numbers of old workers satisfy* $o_N^* > o_D^* > o_A^*$ *and* $w_h(2o_D^*) > w_h(2o_N^*) > w_l(2o_A^*)$.

In addition, when the shock arrives in the anticipatory-dread steady state, wages in the short run drop to below the aftermath steady-state wage.

Proposition 4. $w_l(2o_A^*) > w_l(o_D^* + F(V_A(o_D^*)))$.

Less formally, the supply curve depends on both the current and expected future wage. This is not an issue in the no-shock and post-shock steady state;

workers expect the wage to remain constant. However, in the anticipatory-dread steady state, workers know that there is a chance that the wage will fall. Consequently, they become more reluctant to enter widgeting at any current wage. Therefore, as in Figure 1, the supply curve shifts to the left, and the wage rises while employment falls. When the shock arrives, demand shifts sharply to the left, causing the wage to fall, while the supply curve eventually shifts back to its original location because, in the new steady state, workers again expect the wage to be constant. Steady state is restored with fewer workers and lower wages as the new marginal worker is less averse to working as a teamster than the previous marginal workers were.

Figure 1: Demand for and long-run supply of widgeters in the no-shock, anticipatory dread, and aftermath stages, highlighting steady states.

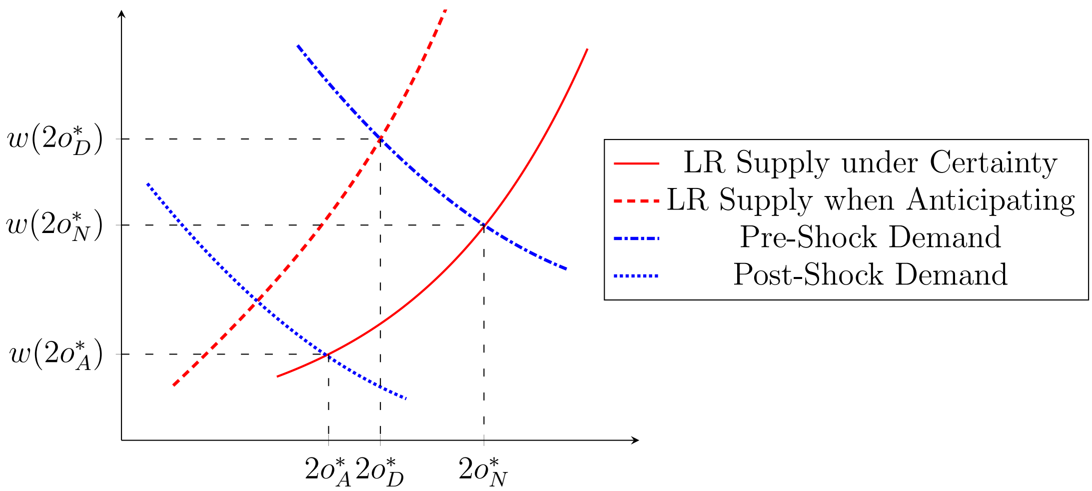
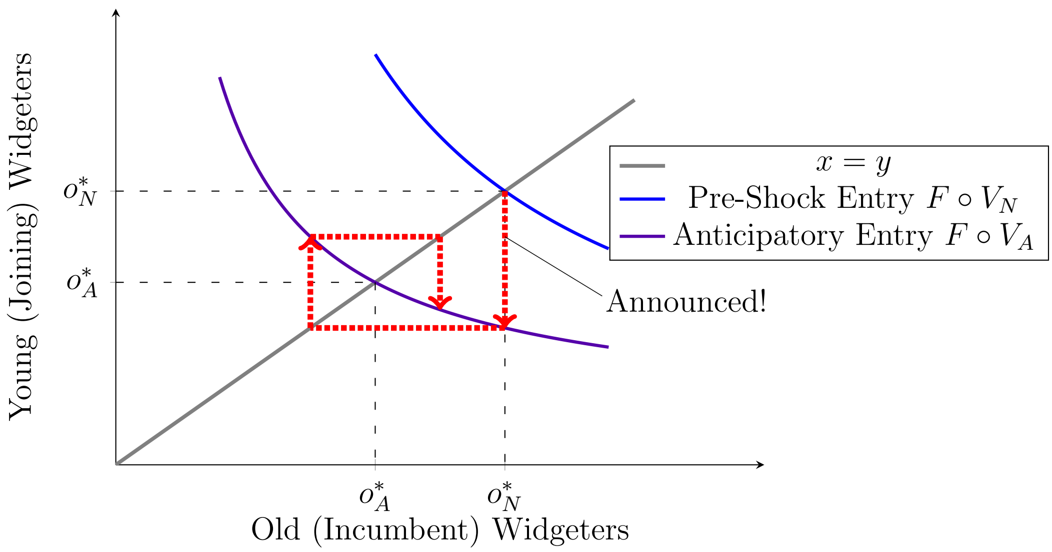


Figure 2 displays the dynamics of the model when the shock is announced. In all periods during the anticipatory-dread stage, wages are higher, and widgeters fewer, than in the old no-shock steady state.

2.2 The Model with Worker Mobility

We now augment the model to allow us to explain changes in worker age profiles. We do this by introducing a probability π that a given worker can change jobs when they turn old. This opportunity arises after workers observe whether the potential transition from the anticipatory-dread stage to the aftermath stage occurred. Thus, if the shock arrives, mobile widgeters may switch to a different occupation. Conversely, if the shock doesn't arrive, other mobile workers may take up widgeting in their second productive period. While our previous results stand

Figure 2: Dynamics of Widgeter Numbers When the Shock Announced



qualitatively unchanged, there are now things we can say about the vintages of workers in the anticipatory-dread steady state.

If $\pi = 0$, no worker can move, and things are exactly as above. If $\pi = 1$, every living worker can choose a new job in every period, and thus the steady states in the no-shock and aftermath stages are reached immediately. There is no risk of getting 'stuck' in a job. Therefore, the anticipatory-dread steady state coincides with the no-shock steady state. In both the $\pi = 0$ and the $\pi = 1$ cases, in each steady state, the numbers of young and old widgeters are equal. This also applies in the no-shock and aftermath steady states when $\pi \in (0, 1)$, as the wage is constant and there is no uncertainty.

However, when $\pi \in (0, 1)$, in the anticipatory-dread steady state, the number of young widgeters is less than the number of old widgeters. To see this, note that when the present widgeting wage is w_t and the next period's wage w_{t+1} is believed to be stochastic (depending on shock arrival), a worker with per-period widgeting disutility ϑ becomes a widgeter if

$$\overbrace{\underbrace{w_t - \vartheta}_{\text{today}} + \delta \underbrace{(1-\pi)E[w_{t+1} - \vartheta]}_{\text{tomorrow, immobile}} + \delta \underbrace{\pi E \max\{0, w_{t+1} - \vartheta\}}_{\text{tomorrow, mobile}}}^{\text{payoff, starting as a widgeter}} \geq \overbrace{\underbrace{0}_{\text{o.o.}} + \delta \underbrace{\pi E \max\{0, w_{t+1} - \vartheta\}}_{\text{tomorrow, mobile}}}^{\text{payoff, starting at outside option}} \tag{8}$$

or simply

$$\vartheta \leq \frac{w_t + \delta(1-\pi)E[w_{t+1}]}{1 + \delta(1-\pi)}. \tag{9}$$

Thus, the number of young widgeters is

$$y_t = F\left((1+\delta)\frac{w_t + \delta(1-\pi)E[w_{t+1}]}{1+\delta(1-\pi)}\right). \tag{10}$$

Correspondingly, mobile old workers choose to be widgeters when

$$\vartheta \leq w_t, \tag{11}$$

so that a fraction

$$F((1+\delta)w_t) \tag{12}$$

works in the occupation. Thus, the total number of old widgeters is

$$(1-\pi)y_{t-1} + \pi F((1+\delta)w_t). \tag{13}$$

Therefore, there are more old widgeters than young if

$$(1-\pi)y_{t-1} + \pi F((1+\delta)w_t) > y_t. \tag{14}$$

In the anticipatory-dread steady state, $y_t = y_{t-1}$ so using (10) this reduces to

$$F((1+\delta)w_t) > F\left((1+\delta)\frac{w_t + \delta(1-\pi)E[w_{t+1}]}{1+\delta(1-\pi)}\right), \tag{15}$$

which we know to be true from the fact that F is strictly increasing and $w_t > E[w_{t+1}]$ due to (an analog of) Proposition 4. Thus, in the anticipatory-dread steady state, there are more old than young workers.

Our model differs in two important ways from models in which adversely shocked occupations age because young workers are less likely to enter but occupation-specific human capital restricts exit by older workers. First, the aging occurs in anticipation of the shock. Second, older workers become more likely to enter and less likely to leave. The proportion of older workers employed as widgeters can even rise, although this depends on parameters.

Showing increased entry of older workers in the anticipatory dread stage is trivial. In the no-shock and post-shock periods, no worker changes occupation. In the anticipatory-dread stage, some older workers enter. The next proposition shows that for some parameter values, there are more older workers in the anticipatory-dread steady state than there are in the no-shock stage. In particular, we show this *must* be the case with high enough mobility.

Proposition 5. *There is some $\underline{\pi} > 0$ such that $\pi \in (\underline{\pi}, 1)$ implies that $o_D^* > o_N^*$.*

Thus, while the risk of obsolescence reduces the number of young workers in the occupation, the attractive force of obsolescence rents can make the occupation have *more* older workers than before the shock is announced. We view this as a possibility that would be hard to replicate in other models.

With minor modification, our model predicts that the retention of old workers is higher in the anticipatory dread stage than in the no-shock stage. To generate mobility in the no-shock world, we can add a small preference shock between periods. Fewer old workers would leave in the anticipatory-dread stage than in the no-shock stage. The marginal old worker is indifferent between leaving and staying in the no-shock world; but, having learned of the shock's non-appearance, this marginal worker strictly desires to stay in the anticipatory-dread steady state.

2.3 A Summary of our Empirical Predictions

In the following sections, we use the theory to study the effect of pending arrivals of motor trucks on teamsters (in section 3), the effect of the threat of computerization on at-risk occupations[2] (in section 4), and - speculatively - of autonomous trucks on truckers (in section 5). In each case, we attempt to establish that there is a period during which the new technology has not been widely adopted but workers in legacy occupations are aware of its pending arrival.

Our model makes several testable predictions about the behavior of the labor market as it transitions to 'anticipatory dread', which we proceed to test where the data allow. Our main predictions revolve around three observables: wages, aggregate employment, and the age distribution of workers.

We predict that (i) wages rise, creating an "obsolescence rent", that (ii) employment falls, and that (iii) the age distribution of workers shifts to the right, due to (a) younger workers in other occupations reducing their entry more sharply than older workers, and (b) younger workers in the affected occupation increasing their exit rate more sharply.

To the best of our knowledge, none of the papers on adjustment to technological shocks has focused on these predictions. The summary statistics in Feigenbaum and Gross (2022) show that as AT&T adopted mechanical switching technology, the proportion of female operators in the telephone industry who were 16-25 fell from 80% in 1910 to 30% in 1940. Bessen et al. (2023) find that older workers are hurt more when their firm introduces automation; this statement is related to, but not equivalent to, our predictions regarding mobility. Similarly, Porzio et al. (2022) documents the "greying" of the agricultural industry with the decreased

[2] As defined by Frey and Osborne (2017)

entry of younger workers. Our study identifies a different mechanism and allows for the possible increased entry and reduced exit of older workers.

We will also draw loosely on Cavounidis and Lang (2020) to predict that, relative to older workers in the negatively shocked occupation, younger workers are more likely to move towards occupations positively affected by technological change and less likely to move to low-skill occupations. In that model, workers invest in a multidimensional profile of skills. Workers respond differently to a shock to the value of skills depending on their age when the shock hits. First, as in Ben-Porath (1967), older workers maximize over a shorter horizon and, therefore, benefit less from investing in positively shocked skills (the horizon effect). Second, older workers have invested more heavily in skills and have more to lose from shifting to jobs that are very different from the one that maximized their pre-shock earnings (the inertia effect). Thus, we anticipate that younger teamsters will be more likely to take up the new occupation, driving a motor truck, while older teamsters will choose to enter closer occupations such as farmer or laborer.

3 Teamsters

3.1 The Rise of Motor Trucks

The arrival of motor trucks (or 'trucks' when there is no risk of confusion) was heralded long before they became widely available and used. In 1895 Thomas Edison declared that it was "... only a question of time when the carriages and trucks in every larger city will be run with motors." (quoted in Montville (1971), p. 378) The first commercial truck was purchased in 1897 (ibid p. 382), but it was not until much later that the use of motor trucks became widespread. The issue was not whether motor trucks could be built, which had certainly been demonstrated by the end of the 19th century, but if and when they would become commercially viable for local freight hauling. Moreover, whether motor trucks would be driven by steam, electricity, or gasoline remained to be determined. Steam lost out early, but competition between electricity and gasoline continued well into the 20th century (Mom and Kirsch 2001).

The use of both cars and motor trucks in the United States grew rapidly in the first three decades of the 20th century, but, as shown in Figure 3, the rise of cars preceded (gasoline and electric) trucks. In 1910, there were almost 460,000 registered cars but only about 10,000 registered trucks. By 1920, there were over eight million cars but just over one million trucks. In 1929, on the eve of the

Great Depression, there were 23 million cars and about 3.5 million trucks. In comparison, in 1995, the ratio of registered cars to trucks was about 1.8.

Of course, there was no single year in which transportation of people and freight in the U.S. transitioned from horse-drawn vehicles to motor trucks. Still, in 1916, just before the U.S. entry into World War I, there were only 250,000 trucks. But the war demonstrated their value. France and Britain purchased large quantities of trucks from American manufacturers, and the United States followed a crash course in designing standardized trucks for military use (Utz 1919). Industry produced thousands of trucks. The experience showed using trucks was feasible (Smiley 2004). The war's end meant the military no longer needed significant production capacity created to meet its demands. Moreover, many military trucks were sold for civilian use and glutted the market until 1921 (Mom and Kirsch 2001). Between 1918 and 1919, registrations increased by almost 300,000, a gain not matched again until 1924.

By 1920, the rise of motor trucks had not yet dramatically decreased demand for teamsters. By our calculation, the 1910 Census includes 421,983 teamsters compared with 350,657 in the 1920 Census. This contrasts markedly with occupations affected by the rise of passenger vehicles. Over the same period, the number of people employed as hostlers and stablehands fell from 63,000 to 19,000, and carriage and hack drivers fell from 35,000 to 10,000. In contrast, chauffeurs increased from 46,000 to 285,000. Consistent with Cavounidis and Lang (2020), among workers who left carriage and hack driving, those who became teamsters were disproportionately older workers.[3]

The sharp decrease in teamster employment occurred between 1920 and 1930. By 1930, helped by the development of pneumatic truck tires, the rise of trucks had dramatically reduced the number of workers employed as teamsters. The number of teamsters collapsed to 177,815, about half the number in 1920.

We searched *Scientific American* for articles with 'truck' in their title and 'motor' in the body or title. From 1901 through 1910, this produced 11 articles, of which we judge only 6 to be about what we would recognize as trucks. Five are very brief, mostly a single paragraph. The exception is a 1909 article (Rogers 1909) arguing that motor trucks were superior to horse-drawn trucks in New York City because they could cover more territory. Still, the article also warned, "Two weeks at the factory is not sufficient to change a stable hand into a competent driver," and stressed the importance of proper maintenance, the risks of overloading, and issues

[3] Carriage and hack driver was a very small occupation; workers moving from carriage and hack drivers to teamsters accounted for less than 1% of the total entry to teamsters.

with roads. Only an adventurous businessman would come away from reading the article with a feeling that it was time to purchase a fleet of motor trucks.

Between 1911 and 1920, 96 articles met our criteria, almost all about vehicles recognizable as motor trucks. A 1913 article comparing the cost of horses, electric trucks, and gasoline trucks (Ritchie 1913) generally favored electric trucks. Still, it stressed that "It is practically impossible to pre-determine what will be the total annual cost of operating a truck at given rating without knowing what will be the requirements of the service, the nature of the road and the general method of handling and repairing for the cars." Horses pulling 1/2 ton and 2 tons could go further on $1 of expense than the same size gasoline truck, although not as far as the equivalent electric truck. Helford (1914) argued that, since they might have difficulty raising the requisite funds to purchase a motor truck, businessmen might want to buy on an installment plan.

A 1918 article in *Scientific American* (The Washington Correspondent of the Scientific American 1918) captures our view. "Prior to the war, the motor truck was making steady progress towards ultimate complete employment. ... But the war accelerated its adoption, perhaps by twenty years." The article further argued that American roads were woefully inadequate for truck traffic.

To complement our investigation into the evolution of anticipation for trucks, we analyzed newspaper articles from the 1910s and 1920s, as newspapers cater to a different readership than *Scientific American*. The timing of shifts in anticipation reflected in newspapers is consistent with what we find in *Scientific American*: the attitudes towards replacing horses with trucks remained largely conservative until the end of World War I. For instance, an article from 1915 still considered the possibility of employing a "mixed system of horses and motors" to replace horses (Boston Evening Transcript 1915). It was not until the war's end that a marked shift in attitudes towards trucks became evident in newspapers. In a 1919 article, the founder of a tire company explicitly stated that "it was the war which really roused manufacturers to the value of the motor truck for ordinary transport" (Firestone 1919). Articles published during this period displayed a more receptive and optimistic attitude toward trucks.

Our interpretation is that between 1910 and 1919, it became increasingly clear that motor trucks were "on their way." The experience of World War I, including the direct observations of returning soldiers and the injection of trucks into the civilian market, should have made it apparent that trucks would supplant horse-drawn vehicles in local freight markets. By 1930, they had largely done so. However, the timing was uncertain since trucks required higher quality roads, which depended on local governments' willingness to undertake the expense. Ultimately, trucks would displace trains in the intercity market, but that transition occurred later. In 1929, intercity trucking accounted for somewhat more than one percent of the ton-miles of freight hauled, but it was growing at 18 percent per year (Smiley 2004).

3.2 The Power of the International Brotherhood of Teamsters

Our model assumes a competitive labor market, but teamsters unionized early in response to low pay and miserable conditions.[4] Still, even in 1920, IBT membership, which included occupations other than teamsters, was less than 30 percent of our estimate of the number of teamsters. Over half of the members of the early union were located in Chicago, where the union was most contentious and regarded by some commentators as highly corrupt. In 1905, a strike by Chicago teamsters left them "utterly defeated and crushed" (Leiter 1957, p. 28).

Nevertheless, the situation remained distinct in Chicago, where many unions remained separate from the International Brotherhood of Teamsters (IBT). Especially towards the end of our period (1928-1935), there was considerable concern about the extent of racketeering and gangster control, including Al Capone's gang, of some of the independent unions. It is not clear that these unions were focused on members' wages. Therefore, for robustness, we will experiment with excluding Chicago from some of our estimates.

By the time our wage data begin, the union president, Daniel Tobin, was well aware of market pressures:

> The relatively conservative attitude of Tobin is reflected in his notions concerning wages. In 1915, he wrote: "... it is impossible for unions to go on year after year endeavoring or expecting to obtain an increase in wages and shortening of working hours" since many workers are getting "... as much as the industry can afford to pay." He subsequently adhered to this position when he had to participate in the bargaining negotiations of some IBT locals. (Leiter 1957, p. 44)

Moreover, there was a substantial nonunion group that would have influenced the IBT's negotiations. We conclude that, with the possible exception of the Chicago unions, the teamsters union was responsive to economic conditions.

[4] This subsection draws almost entirely on Leiter (1957).

Therefore, we should expect patterns similar to those we derive from a competitive model.

We do not claim that the union was powerless. During what we will identify as the anticipatory dread period, there were frequent small strikes and some important ones, most notably the Indianapolis Street Railway Strike of 1913, in which the teamsters participated. The American Federation of Labor reported that in 1914 and 1915, teamsters engaged in 36 strikes involving approximately 3,600 workers (Bureau of Labor Statistics 1916). Still, in 1916, James Casey, the founder of UPS (then the Merchants Delivery Service and subsequently the United Parcel Service) asked the teamsters to organize his workers. This is inconsistent with a militant IBT (International Brotherhood of Teamsters 2015).

3.3 Employment: Identifying Anticipatory Dread and the Aftermath

Based on the previous account, we see the no-shock period ending sometime around 1910. The shock arrived shortly after World War I, roughly in 1919. The anticipatory dread period fell in between. In contrast with our formal model, the arrival hazard of motor trucks was not constant but rose rapidly between 1910 and 1919, and, of course, the new technology was not adopted instantaneously. Unfortunately, we cannot date the collapse of teamster employment precisely. As we will see, teamster employment fell modestly between 1910 and 1920, consistent with what we expect in the anticipatory dread period, and then collapsed between 1920 and 1930 after the arrival of the shock.

We use the IPUMS 1880, 1900, 1910, 1920, and 1930 full-count census data to estimate teamster employment (Ruggles et al. 2020). Unfortunately, the occupation classification variable (*occ1950*) does not record teamsters consistently over this period.[5] We supplement *occ1950* with two additional variables: *occstr* and *ind1950*, which allow us to identify teamsters more accurately. The variable *occstr* reports the respondent's original (unedited) response, including terms like "teamster" or "teaming". *ind1950* provides consistent industry codes across census waves.

We combine these variables to obtain a more accurate count of teamsters. First, we include workers classified as teamsters using the *occ1950* variable. Then, we add workers whose *occstr* contains the keyword "team." Next, we include workers whose *occstr* contains terms like "driver", "wagoner", "drayman" etc., and

[5]For instance, starting from 1910, teamsters in certain industries were coded as 'laborers' or 'deliverymen,' which resulted in a reduced number of teamsters compared to previous years (Ruggles et al. 2020, 2022).

Table 1: Teamster Employment: 1880-1930

Year	Edwards (1943) male teamsters	Male teamsters	Employed males	Fraction (%)
1880	119,131	153,852	15,119,401	1.02
1890	246,095			
1900	361,308	407,747	23,364,086	1.75
1910	443,735	421,983	30,515,530	1.38
1920	419,450	350,657	32,906,318	1.07
1930	111,178	177,815	38,058,536	0.47

Notes: All the numbers are for males 10 years old and over. Column 'Edwards (1943) male teamsters' is copied from Edwards (1943). Other columns are from the authors' calculations based on full-count censuses. Our approach to identifying teamsters differs from that of Edwards (1943). For example, our estimates include workers classified as "deliverymen in stores" as teamsters while Edwards (1943) does not.
Source: US Census

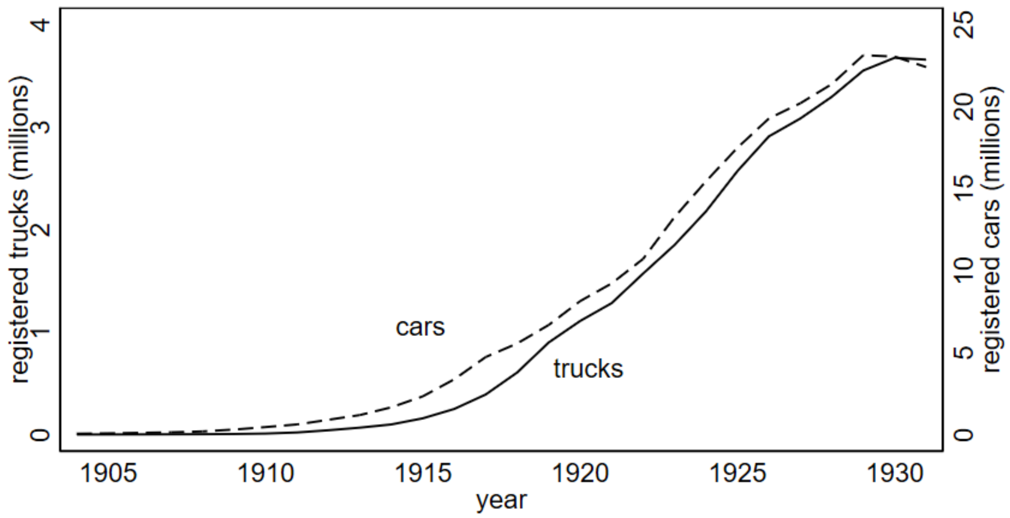
who were employed in the "trucking service" industry according to the *ind1950* variable. Finally, we exclude workers whose *occstr* includes keywords such as "truck", "motor", "hostler", "stable", or "groom."[6]

Table 1 presents teamster employment by decade in absolute numbers and as a fraction of employed males. We focus on the male labor force for the teamster analysis as almost all teamsters were males during this period. Column 2 shows the teamster employment copied directly from the census report (Edwards 1943), while the remaining columns exhibit our own calculations using the full-count censuses. Our estimates closely align with the official reports. The census report documents 361,308 draymen, teamsters, and carriage drivers in 1900 and 443,735 in 1910, while our inferred teamster employment is 407,747 in 1900 and 421,983 in 1910. The census report and our calculations show similar patterns of teamster employment over time. Teamsters increased from 1880-1900 when the economy experienced radical industrial expansion and population growth. Teamster employment was stable from 1900 to 1910, with a slight increase in numbers and a slight decrease in their fraction of all employed males. Absolute teamster employment decreased from 1910 to 1920 and collapsed from 1920 to 1930.

These employment changes are consistent with the distribution of trucks. According to the motor vehicle registration records shown in Figure 3, before 1910, very few trucks were available, and the number of teamsters grew between 1900 and 1910, although teamsters declined as a proportion of the labor force. In the

[6]Stablemen, hostlers, and grooms are workers who care for horses but do not use them to pull vehicles as a principal element of their work.

Figure 3: Registrations of Automobiles and Trucks: 1904-1931



Source: Federal Highway Administration (1997)

late 1910s, the number of trucks began to increase. Some teamsters felt the threat and changed their occupation, but most stayed. From 1920 to 1930, trucks increased dramatically, and it became clear that teamsters were a poor substitute for truckers. Correspondingly, employment collapsed.

In our model's terminology, the period of 'anticipatory dread' began around 1910. The effects of anticipation intensified over the following decade, with the predicted decline in employment (prediction (ii) in section 2.3). The shock finally arrived at the end of the decade, causing employment to crater in the 1920s.

3.4 The Aging of Teamsters: Entrants Got Older, Leavers Younger

As our model predicts (prediction (iii) in section 2.3), during the period of anticipatory dread, the age distribution of workers in the occupation shifted to the right, as being stuck in an occupation with low demand is more costly for young workers. Importantly, again as predicted, this shift began *before* employment collapsed because younger workers bear a higher risk that the shock will arrive while they are still working and will have more work years remaining if it does. Figure B.1 in the appendix shows how the age composition of individuals employed as teamsters changed in anticipation of the shock and after the shock.

We observe some aging of the occupation between 1900 and 1910 when we also observe the first indications that motor trucks are on the horizon. Thus, the occupation began to age even though competition from motor trucks was negligible, with only 10,000 trucks registered nationwide. By 1920, the aging of the occupation, even relative to 1910, was self-evident. From 1920 to 1930, as the number of trucks dramatically increased, employment decreased sharply in both absolute and relative terms, with young workers decreasing more than older workers. Despite the heavy physical demands, driving a team of horses had become an older man's job. Our formal model further implies that after the shock has been in place for a sufficiently long time, the proportion of workers in the occupation should be independent of age in the new steady state. While we do not wish to read too much into the age distribution of the small population of teamsters, we note that this prediction is quite accurate for teamsters in 1960 (see Figure B.2 in the appendix).

The aging of the occupation might be mechanical once we account for reduced entry. If fewer workers enter an occupation, those who remain get older. This is how we understand the implicit model in Dorn et al. (2009). However, we find that the proportion of the very oldest workers who were teamsters was actually higher in 1920 than in 1910, even though the proportion of workers ten years younger was higher in 1900 than in 1910.

Still, our model makes strong predictions regarding changes in entry and exit. Therefore, we examine the age distribution of workers entering and remaining in employment as teamsters (predictions (iiia) and (iiib) in section 2.3). For this exercise, we use the linkage data described in Abramitzky et al. (2022) to link the full-count censuses.

We take 1900-1910 as the reference for movements during a 10-year period and compare these movements to those in 1910-1920 and 1920-1930. For each age, we calculate the number of workers who transitioned from other occupations to teamsters between two consecutive census years. We divide this number by the number of workers who were not teamsters in the earlier census, providing us with the proportion of non-teamsters entering teamster employment for each period. Similarly, for each of the three 10-year periods, we calculate the number of workers who remained as teamsters and divide by the number of teamsters in the earlier census year who remained employed anywhere in the later period. Then, we calculate the entry and retention rates by age as a *proportion* of the rate between 1900 and 1910. In other words, we calculate $rate^a_{j,t}/rate^a_{j,1900-1910}$ where $j = entry$ or $retention$, a denotes age, and $t = 1910-1920$ or $1920-1930$. We choose the proportions because the declines in entry and retention rates are sufficiently large and baseline levels sufficiently different that it is implausible that the counterfactual is a common percentage point decline.

We anticipate that the resulting proportion will be less than 1 for younger workers but increase with age. While most workers should have become less likely to start as teamsters and more likely to exit, the decreased entry and increased exit should be more pronounced for young workers, as they find being stuck in a sunset industry more costly and could, as our model shows, be reversed for older workers. Similar logic applies to the 1920-1930 period, but the difference from 1900-1910 should be larger since teamster employment collapsed during this period, deterring more workers from entering and encouraging greater exit.

Figure 4 shows the results of this exercise and confirms the model's predictions. The left panel shows the entry rate by age in the anticipatory-dread and post-shock periods relative to the earliest period in our data. The right panel is analogous, except that it shows the retention rate. In each case, the horizontal axis shows the age in the later census. For example, age 30 refers to someone 20 years old in the earlier census. We do not include the movements between the 1880 and 1900 censuses because they cover a twenty-year period and, thus, are not comparable to the other periods.

Thus, compared with 1900-1910, in the anticipatory-dread period (1910-1920), the entry rate of 30-year-old workers (20 at the beginning of the decade) to teamster employment is about 66% of the baseline. The relative rate is less than 100% for most age groups. However, it is striking that the oldest workers actually increased their entry rate during this period. They may have anticipated earning high wages and retiring before obsolescence. Similarly, retention of 30-year-old workers (20 years old in 1910) is only about 80% of its baseline rate, but this rate rises and passes 100% among the oldest workers. While it is possible to generate higher retention of older workers in a model in which older workers have occupation-specific capital and reduced demand for the occupation discourages entry by young workers, it is hard to see why older workers would enter in such models. Surprisingly, there is a small range among the youngest workers during which the relative retention rate slopes downwards.

After the shock hit (1920-1930), entry and retention decreased further relative to the 1900-1910 baseline. As expected, the relative rates are all below 100%. Again, except for the very youngest group, the relative rates increase with age.

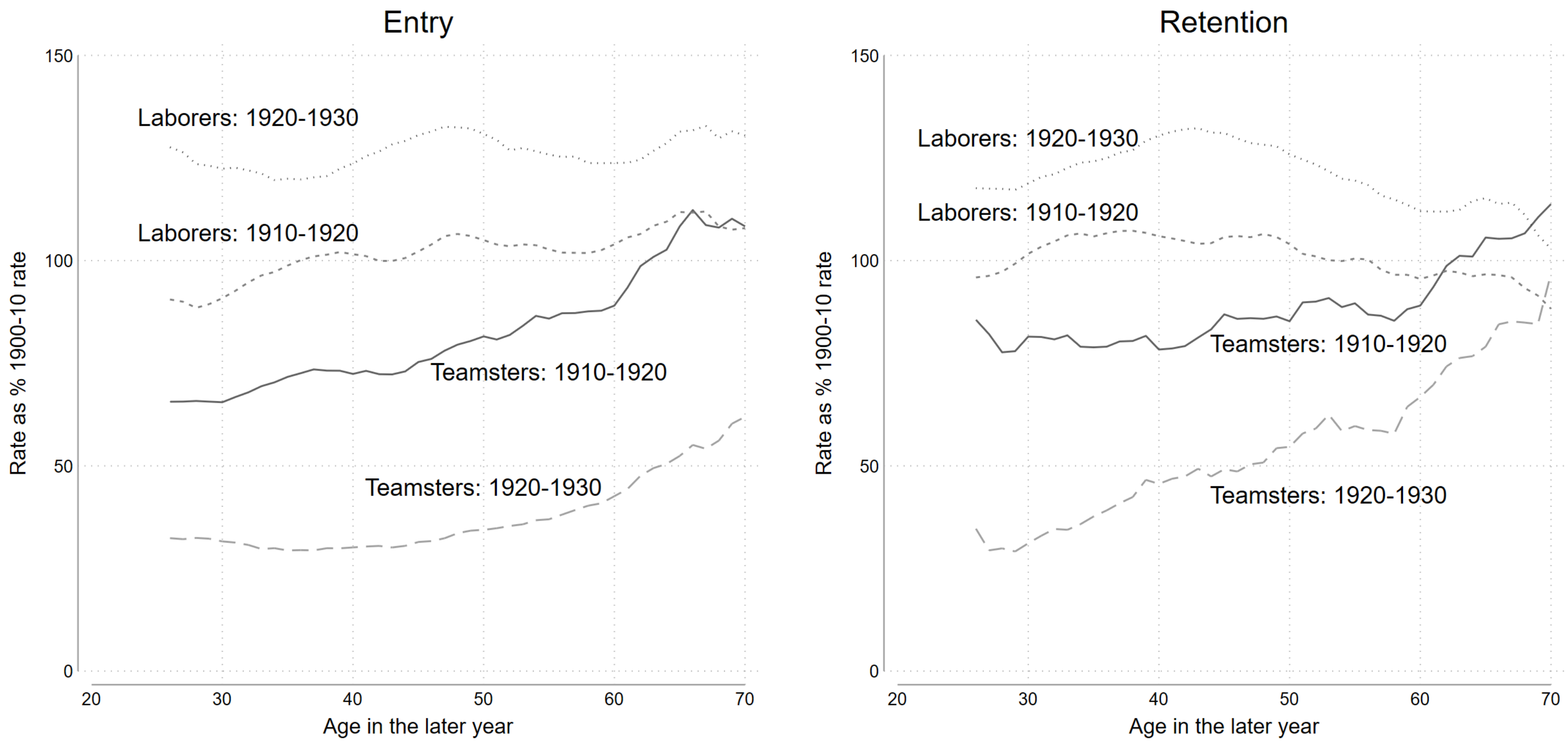
Perhaps older workers were simply less likely to change occupations between 1910 and 1920. To address this concern, Figure 4 also provides the analogous plots for laborers (not elsewhere classified). We choose this occupation because it is large, making the calculations feasible, the largest non-agricultural destination occupation for workers transitioning from employment as teamsters, and the largest source occupation for workers transitioning to teamster employment. Moreover, as the plots reveal, employment of laborers (n.e.c.) did not collapse between 1910 and 1930. Thus, they provide a sensible comparison group for our visual difference-in-differences. The plots for these laborers exhibit very different patterns from those for teamsters. In general, the proportions do not increase noticeably with age. While the entry proportion in 1910-1920 shows a modest upward slope, its magnitude is much smaller than teamsters during the same period.

3.5 Moving to Opportunity or Moving to What's Left?

Cavounidis and Lang (2020) analyze the reaction of individual workers to a shock that lowers the value of one skill and raises that of another. Older workers employed in occupations that are intensive in the negatively shocked skill move away from that skill relatively slowly. Young workers move towards positively shocked occupations relatively rapidly. That model is distinct from the one in this paper. Nevertheless, we draw on that model's intuition to explore mobility patterns into and, especially, out of employment as a teamster. In our context, the negatively shocked occupation is self-evidently teamster. The positively shocked occupation is truck driver.

We note that there has been some research on reemployment of workers following a technology shock at their firm. Feigenbaum and Gross (2022) are closest to us in looking at outcomes by age, but since their age groups are 16-20, 21-25, and 26+, it is not clear that the time-horizon considerations in Cavounidis and Lang apply. Cavounidis and Lang also discuss an 'inertia' effect, which they argue should strengthen rapidly early in one's career, as optimal skill investment is front-loaded. The inertia effect captures the fact that workers are best suited to jobs using skills in which they have already invested and, therefore, pay a significant cost if they retrain for jobs using very different skills. Bessen et al. (2023) find much clearer evidence of adverse effects on workers age 50 and up when their employer automates, but this comes primarily through nonemployment. Bessen et al. do not address occupation changes among reemployed workers.

Figure 4: Teamster Entry and Retention by Age: Relative to 1900-1910



Notes:For teamsters, this figure shows the entry rate (left panel) from non-teamster employment to teamster employment for each period divided by this rate between 1900 and 1910 (in percent). The entry rate is defined as the proportion of employed workers in jobs other than teamsters in year t-10 who were employed as teamsters in period t. The right panel shows the retention rate of teamsters divided by this rate between 1900 and 1910 (in percent). The retention rate is the number of workers employed as teamsters in both t and t-10 divided by the number of workers employed as teamsters in t-10 who were employed in any occupation in t. The entry and retention are calculated in the same way for laborers (nec). The figures show the rates for male workers aged 16-60 in the former year (aged 26-70 in the later year) and who could be matched across censuses. The rates presented in the figures are 5-year moving averages.

Workers who entered employment as a teamster from another occupation came primarily from employment as laborers (not elsewhere classified [n.e.c.]), farm laborers who are wage workers, and farmers (owners and tenants). These are the top three source occupations for all age groups (26-35, 36-45, 46-55, 56-65) and all periods (1900-10, 1910-20, 1920-30) except that in 1910-1920, workers aged 26-35 are more likely to enter from unpaid family farm labor than from paid farm labor, and workers aged 56-65 are more likely to enter from managers, proprietors and officials (n.e.c.). In each age/year, these three occupations account for 44-66% of workers entering teamster employment from another occupation.

Workers who leave employment as a teamster for other employment exit primarily to laborers (n.e.c.), farmers (owners and tenants), truck and tractor drivers, managers, proprietors, and officials (n.e.c.) (see Table 2). These four occupations are the four most common exit occupations, except that few teamsters moved to work as truck and tractor drivers between 1900 and 1910. They account for 38% to 57% of workers leaving teamster employment in all age groups, with higher proportions at older ages.

Table 2: Primary Destination Occupations of Workers Leaving Employment as Teamsters

	Laborer (nec)	Farmers owners & tenants	Truck/Tractor Drivers	Managers, Officials Proprietors (nec)	Total	N
1910-1920						
26-35	12.36	14.99	5.31	5.24	37.9	21,284
36-45	14.16	20.5	4.33	6.63	45.62	19,102
46-55	18.63	21.57	3.33	7.14	50.67	12,473
56-65	21.71	22.51	2.1	7.37	53.69	7,111
1920-1930						
26-35	15.33	9.41	12.84	5.99	43.57	19,870
36-45	17.77	14.46	11.17	8.05	51.45	19,010
46-55	22.52	17.24	8.27	8.19	56.22	13,168
56-65	24.9	19	4.93	7.72	56.55	8,269

Notes: nec = not elsewhere classified.

Source: Authors' calculations based on pairwise matched Census data.

As predicted by Cavounidis and Lang (2020), we observe a strong negative age gradient in the proportion of exiting teamsters who enter the new occupation. Recall that this gradient is on top of the higher rate of exit by young teamsters. In 1910-20, 5% of the youngest group but only 2% of the oldest who exited became truck or tractor drivers. In the last decade, the youngest group was eight percentage points more likely than the oldest to exit this way.

It is also striking that the age gradient for moving to a declining occupation, farmer, increased. Between 1910 and 1920, among exiters, movement to farming shows a slight positive age gradient. Between 1920 and 1930, there is a clear upward slope.

By way of comparison, we show similar results for laborers (n.e.c.) in Table B.1. Conditional on exiting, we would expect similar patterns of movement with respect to farming and managers, officials, and proprietors (n.e.c.), as we do. However, teamsters, especially younger ones, are noticeably more likely to become truck drivers since the newly developed occupation draws on their prior knowledge of city streets and skill at loading and unloading trucks.

3.6 Wages Rose and then Fell

To investigate prediction (i) in section 2.3, we obtain the wage data for teamsters and other occupations from bulletins of the Bureau of Labor Statistics.[7] These bulletins report the union scale of wages annually in selected trades and cities. Neither the set of trades nor the cities covered are consistent across years. We focus on the weekly wage of teamsters from 1913-1931 in Boston, Chicago, New York, St. Louis, and San Francisco, each of which has a complete time-series for two-horse teamsters.[8] We note that Leiter (1957) used only Boston, New York, St. Louis, and San Francisco, presumably because Chicago had some militant and corrupt unions. We show that our results remain robust when Chicago is excluded (see Figures B.4 and B.5 in the Appendix). Unfortunately, the BLS did not collect wage data for teamsters between 1901 and 1912, and the data before 1901 are not comparable to the later data. Similarly, we have no wage data for 1932-1939, and the later data are not comparable to those we use.

We use "all trades" and "close trades" to compare the wages of teamsters and other workers. All trades, the average of all the trades and cities covered in each BLS bulletin, has the advantage of being more stable and reflecting an aggregate trend covering more cities and occupations. On the other hand, complete teamster wage data are only available for the five cities, wages of all trades include additional cities, and the wages in some included trades are not directly comparable to those

[7]The Bulletin of the United States Bureau of Labor Statistics Nos. 143, 171, 194, 214, 245, 259, 274, 286, 302, 325, 354, 388, 404, 431, 457, 482, 515, 540, and 566 (Bureau of Labor Statistics 1914-1931).

[8]Cincinnati, Ohio and Philadelphia, PA also have complete time-series. Cincinnati was too small, while data on Philadelphia consists of two types of two-horse teamsters (general teamsters before 1921 and lumber drivers from 1921). Hence, its data are not comparable over time and thus excluded.

of teamsters. Also, the sets of trades and cities are inconsistent over time for "all trades".[9]

For close trades, we used occupations with wages close to teamster wages in 1896-1900 that had data for at least four of our five cities for the entire period. We define 'close' as a daily rate below $3 in 1896-1900. The highest daily rate for teamsters in that period was $2.74 in New York in 1898. Teamsters earned close to the lowest wages among those for whom we have wage data, so this restriction mainly eliminates higher-pay occupations. The resulting occupations are building trades laborers, carpenters, hod carriers, inside wiremen, painters in the building trades, and platen and cylinder press feeders.[10]

Figure 5 shows the city average wage levels for two-horse teamsters relative to close trades in the five cities. Compared to close trades, the teamster wage began increasing in 1917, peaked in 1919, collapsed after 1919, and then slightly recovered after 1927. Teamsters' wages relative to all trades have a similar pattern. The relative wage in 1931 was slightly lower than in 1913 for all trades and much lower for close trades. We do not, however, claim that the only reason for relative wage changes between 1929 and 1931 was the long-run response to the arrival of motor trucks. Apart from economy-wide events, teamsters' age composition changes could also have played a role.[11] More generally, we readily admit that we cannot control for compositional changes. Employers might have been willing to negotiate higher wages for an older and more experienced workforce. If compositional changes were important for explaining wage changes, this would reinforce

[9]For example, the dataset covered only 41 cities in 1913. This number increased over the years, reaching 66 in 1920 and maintaining that count from 1920 to 1927. Subsequently, it rose to 67 in 1928-1931. According to BLS reports, these cities were considered "important industrial cities" and were "the largest in the respective sections of the country." The coverage of trades also changed over time. For example, "laundry workers" were not included until 1918. Additionally, some trades were excluded in some years due to data availability.

[10]Based on descriptions from the Bureau of Labor Statistics, building trades laborers are those who perform tasks involving physical labor in building trades; carpenters are those who construct, erect, install, or repair structures and fixtures made of wood and comparable materials; hod carriers are those who carry supplies to masons or bricklayers; inside wiremen are those who install, maintain, and repair electrical wiring, equipment, and fixtures indoors; painters (building trades) are those who apply paint, stain, and coatings to walls and ceilings, buildings, large machinery and equipment, and bridges and other structures; cylinder press feeders are those who load paper into the feeding tray of a printing press using a cylinder press; platen press feeders are those who load paper into the feeding tray of a printing press using a platen press.

[11]Figure B.3 in the appendix shows the results by occupation relative to close trades in Boston, Chicago, New York, St. Louis, and San Francisco, when reported by the BLS, and all trades in the full set of cities surveyed by the BLS, again subject to the caveat that the trades and cities are inconsistent from year to year. New York has no data on hod carriers; San Francisco has no data on inside wiremen in 1921; St. Louis has no data on press feeders (platen) in 1918-1919, and Boston has no data on press feeders (platen). The results for most individual occupations are consistent with our expectations except for building trades laborers.

Figure 5: Wage differences between teamsters and other occupations (averages)

Notes: The figure shows wage differences between teamsters and the average wages of close trades or all trades. Wage differences are measured by subtracting the log weekly wage of close trades or all trades from the log weekly wage of teamsters. "Close trades" is the simple average of the log wage of all the close trades: building trade laborers, carpenters, hod carriers, inside wiremen, painters in building trades, and the two types of press feeders. These occupations are used as comparisons because 1) their wages were close to teamsters in 1896-1900, 2) they have data for at least 4 cities of interest, and 3) they have available data in 1913-1931. "All trades" is the average of all the selected trades and cities covered in each BLS bulletin. The sets of trades and cities are inconsistent over time for "all trades."

our findings regarding who joins and who leaves employment as a teamster.

To examine the statistical significance of the changes, we estimate the equation below:

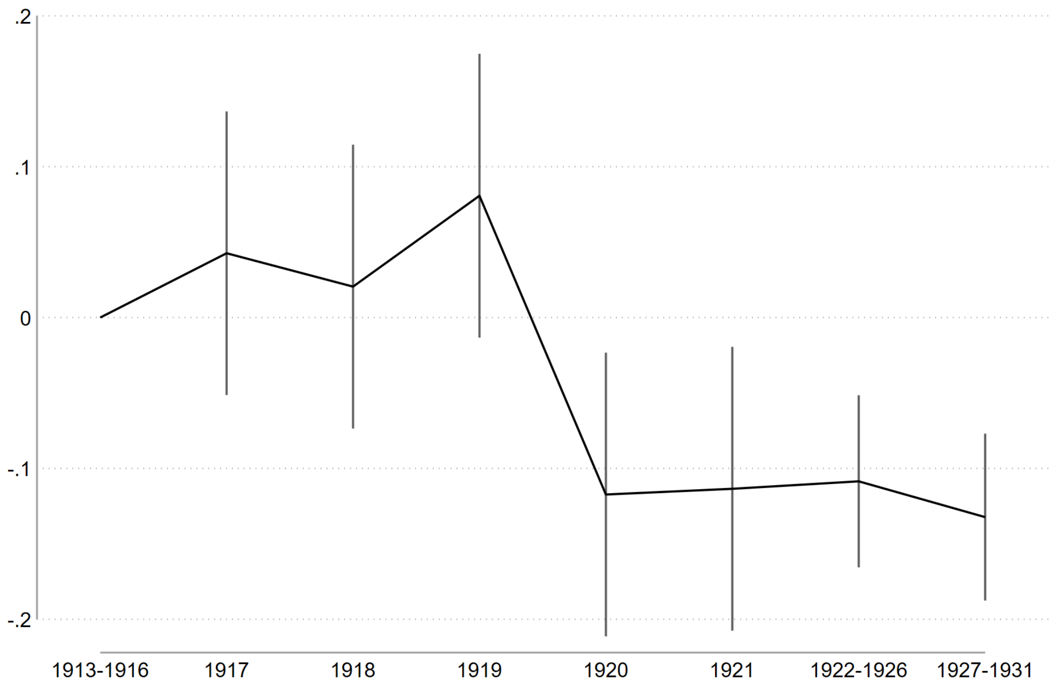
$$\begin{aligned}\ln weeklywage_{jct} = \sum_{\tau=1917}^{1921} \beta_\tau Teamster \times \mathbb{1}\{\tau = t\} + \\ \beta_{1922-26} Teamster \times \mathbb{1}\{1922 \leq t \leq 1926\} + \\ \beta_{1927-31} Teamster \times \mathbb{1}\{1927 \leq t \leq 1931\} + \\ \mu_{ct} + \gamma_{cj} + \eta_{jct}\end{aligned} \tag{16}$$

where $lnweeklywage_{jct}$ is the log weekly wage for occupation j in city c in year

t, μ_{ct} are city-year fixed effects, and γ_{cj} are city-occupation fixed effects. βs are the coefficients of interest. 1913-1916 is the reference period. β_t (t = 1917, ..., 1921) measures the deviation of the teamster wage in year t from the aggregate wage trend, which can be attributed to some time-variant idiosyncratic shocks faced only by teamsters. $\beta_{1922-1926}$ and $\beta_{1927-1931}$ reflect the wage deviations in a similar sense for 1922-1926 and 1927-1931.

Figure 6 shows the estimation results. Consistent with the previous figures, teamsters' relative wages increased after 1917. In 1919, the wage increase was positive and marginally significant compared to 1913-1916. The estimated 8.1% increase in teamsters' relative wage over three years is nontrivial. After 1920, teamster wages were lower than the reference period and showed no obvious recovery in the later periods. The 19.8% drop from 1919 to 1920 indicates the strength of the shock.

Figure 6: Wage differences between teamsters and other occupations



Notes: The figure shows the estimation results using Equation (16). Bars reflect 95% confidence intervals. The regression is weighted by the cities' male labor force.

Of course, it would be foolish to suggest that the wage increases in 1917-1919 can be explained only by teamsters' fear of obsolescence. For example, the run-up to the U.S. entry into World War I and the return of military equipment after the war might have increased demand for teamsters to haul military-related goods and equipment. To address this concern, we examine "revenue-tons of railroad freight." Essentially, this counts the total tons of freight shipped by rail but does not double-count freight transferred from one train to another. The amount shipped was essentially flat from 1916 through 1920, except for a dip in 1919 (U.S. Bureau of the Census 1960) (p. 431). It is hard to reconcile the 1916-19 run-up of wages and their collapse in 1920 with the pattern for freight shipment.

4 Evidence of Dread in Contemporary Data

In this section, we draw on Frey and Osborne (2017) to identify occupations under threat from computerization and show that they exhibit patterns consistent with anticipatory dread. That paper used data from 2010 to assess the probability that each of 702 occupations would be displaced by computerization by 2030. The estimates were first released in a 2013 working paper. We are able to match the Frey and Osborne sample to 413 of the 441 census occupations in the Current Population Survey (Flood et al. 2023).

We further restrict the sample to the 301 largest occupations, dropping occupations with small samples. We begin our analysis with data from 2005 to mitigate the effects of changes to the CPS sample and design.[12] Additionally, we restrict the sample to workers aged 16-75 who are employed in one of the specified occupations, excluding those who are self-employed,[13] as well as those employed in government, armed forces, or as unpaid family workers.

4.1 Validating Frey and Osborne (2017)

Notably, the Frey/Osborne estimates do predict employment decline from 2013 to 2019. If we regress the log employment change from 2005 to 2019 on the Frey/Osborne probability (hereafter, the probability), the coefficient is $-.53$ with a standard error of .06. However, we may reasonably be concerned that the authors were aware of this information when training the model. Therefore, we look at the log employment change between 2013 and 2019, a period for which the Frey/Osborne estimates are clearly predictive rather than retrospective; the coefficient is $-.20$ with a standard error of .04. Of course, the authors might just

[12]The sample change was completed during 2005. Based on Shoemaker (2004), we estimate that in 2005 83% of the sample was based on the new design.

[13]Self-employed workers are excluded because their earnings data are unavailable, which is essential for the analysis of earnings changes.

have predicted the continuation of trends that were already underway. Therefore, we limit the sample to the 171 occupations that gained employment between 2005 and 2013. The resulting coefficient is $-.22$ with a standard error of .05.

4.2 Evidence of Anticipatory Dread: Slow Employment Growth

So far, we have established that the Frey/Osborne probability predicts employment decline even in occupations that were not already declining. However, it is possible that only a subset of occupations that experienced a technology shock between 2013 and 2019 satisfy the prediction. To limit this possibility, we further restrict the sample to 152 occupations for which $\Delta \ln(emp)$ is greater than $-.2$, roughly -18%. Even here, the regression of employment change between 2013 and 2019 on the probability is $-.16$ with a standard error of .04. The coefficient remains negative and statistically significant at the .05 level if we further restrict the sample to 115 occupations with positive employment growth after the release of the Frey/Osborne estimates.

We also find that increased computerization risk is associated with lower employment growth at the median and 90th percentiles. When applied to occupations with positive employment growth from 2005 to 2013, both coefficients are $-.22$, although the coefficient at the 90th percentile is imprecise and significant at only the .05 level.

Table 3 shows the result of regressing log employment, ln weekly earnings, and mean age in occupation i in year t on the probability interacted with year and on occupation and year dummies. For the moment, we concentrate on the first of these. The left side of the table uses the data from the entire period; the right side restricts the data to 2013-19.

When we include all 301 occupations and the entire period, we find that going from a 0 to 1 probability of computerization reduces employment growth by 3.5% per year, or about 39% over 14 years. Restricting the sample to occupations that grew between 2005 and 2013, reduces this difference to 2.3% per year or about 27% over 14 years. Further restricting the sample to occupations with no more than an 18% drop in employment after 2013 has only a modest effect on the results.

Restricting the sample to the second half of our period has little effect on our results except to make them more imprecise. In no case do the differences between the full and partial period estimates differ at anything approaching statistical significance.

4.3 Earnings Rose Faster Even Though Employment Increased More Slowly

Although we find slow employment growth in at-risk occupations that had not suffered from large shocks, it is possible that the Frey/Osborne probability proxies for a demand shock; computerization of the occupation might be in its early stages. If this were the case, we would expect earnings to fall. Therefore, we regress the change in log weekly earnings on this probability. We again limit the sample to occupations with positive employment growth between 2005 and 2013. The resulting coefficient is .036 with a standard error of .019, significant at the .1 level. We also find that log usual weekly hours increase. Although not modeled formally, this is consistent with fewer workers remaining in the occupation and, therefore, does not contradict our expectations. When we control for the change in hours, the coefficient on the probability falls to an imprecisely estimated .022. We can restrict the sample to occupations that we are increasingly confident did not experience a shock. The coefficient rises to .027 when we require that the change in log employment was greater than $-.2$ and to .037 when we require the change to be positive. In sum, hours and earnings both increased faster in more threatened occupations.

When we regress log weekly earnings on the probability interacted with a time trend along with occupation and year dummies, we again find strong evidence that earnings were growing faster in the more threatened occupations. As shown in the second line of each panel of Table 3, for the full set of 301 occupations, log weekly earnings rose about .37% per year faster in an occupation with a 100% chance of computerization than in one with 0% chance or about 5.3% over the entire period. As we restrict the sample, this annual difference falls to .21 and .22 or 3.0% and 3.2%. Although we continue to focus on the more restricted samples, we note that the higher wage growth in the full sample would not be suggested by a simple model in which the excluded occupations had been subjected to a negative demand shock.

Strikingly, the earnings effect is even larger if we restrict the sample to the second half of our period. Using all 301 occupations, the coefficient on probability*time rises from .37 to 1.12. This difference is significant at any conventional level. When we restrict the sample to occupations that grew in the first half of our period, the coefficient is noticeably smaller but is also larger than the estimate for the full period for this sample (the difference is significant at the .1 level). Further restricting the sample to occupations with no more than modest employment declines in the later period somewhat raises the coefficient. Again, the coefficient is noticeably larger for the later period than for the full sample, and the difference between the full and later periods is statistically significant at the .05 level.

Table 3: Computerization Risk Lowers Employment, Raises Earnings and Mean Age

	2005 - 2019			2013 - 2019		
	Probability * year/100	Obs.	Mean Dep. Var.	Probability * year/100	Obs.	Mean Dep. Var.
All						
log emp.	-3.505	4515	14.525	-3.153	2107	14.547
	(0.193)			(0.413)		
log earn.	0.371	4515	5.866	1.115	2107	5.878
	(0.062)			(0.118)		
mean age	6.419	4515	40.436	9.537	2107	40.946
	(1.158)			(3.555)		
Positive Employment Growth 2005-13						
log emp.	-2.267	2565	14.629	-2.943	1197	14.722
	(0.201)			(0.502)		
log earn.	0.210	2565	5.926	0.561	1197	5.934
	(0.072)			(0.224)		
mean age	4.421	2565	40.380	11.214	1197	40.814
	(1.509)			(4.435)		
Positive Employment Growth 2005-13 & Employment Growth 2013-19 > -18%						
log emp.	-2.037	2280	14.782	-1.976	1064	14.881
	(0.206)			(0.443)		
log earn.	0.225	2280	5.908	0.657	1064	5.916
	(0.072)			(0.226)		
mean age	5.480	2280	40.410	8.688	1064	40.849
	(1.466)			(4.114)		

Notes: Each estimate controls for occupation and year fixed effects. Robust standard error are provided in parentheses. *Abbreviations:* Obs.=Number of Observations; Dep. Var. = Dependent Variable; emp. = employment; earn. = weekly earnings.

4.4 Composition Only Partially Explains the Earnings Increase

One concern is that the earnings increase reflects composition effects. Older workers tend to earn more than younger workers. While the magnitude of the aging effect we find is unlikely to fully explain the earnings effect, perhaps other demographic changes account for the apparent earnings gain. Indeed, recent evidence (Böhm et al. 2024) suggests that the quality of workers who remain in declining industries exceeds that of those who leave.

We turn to individual data to address this concern. Our sample consists of workers in the 152 occupations that were sufficiently large, had positive employment growth between 2005 and 2013 and did not experience an employment drop of more than 18% between 2013 and 2019.

We begin by regressing individual log weekly earnings on the probability interacted with a time trend and control for occupation and year fixed effects. We cluster the standard errors at the occupation level. This specification resembles the occupation analysis except that it implicitly weights by the size of the occupation. As shown in the first column of Table 4, the resulting coefficient on the interaction term (divided by 100 as in Table 3) is .32 and is highly significant. This coefficient is somewhat larger than the one we obtain when we weight occupations equally. The fourth column of the table repeats the exercise but limits the sample to the second half of the period. As we found when we weighted all occupations equally, this noticeably increases the coefficient, in this case by a factor of about three.

Columns (2) and (5) add a large set of demographic controls (log age, calendar month, state, 6 marital status categories, 25 race groups, gender, and 15 education levels). For the full period, the estimate declines notably and falls just short of significance at the .1 level. For the period after the Frey/Osborne predictions, the coefficient and standard error are virtually unchanged.

Although hours may respond endogenously to the threat of a shock, in columns (3) and (6), we control for log weekly hours and a dummy for working full-time (at least 35 hours/week). This somewhat increases the coefficient for the full period, which is again significant at the .05 level. For the later period, the coefficient is reduced by close to a third but remains highly significant.

The specifications in Table 4 assume that the controls have the same coefficients in all occupations. At the cost of many degrees of freedom, we can interact all of the controls with occupation dummies.

We proceed in two steps. First, we regress log weekly earnings in each occupation separately on our controls and year dummies. We then regress the occupation/year coefficients on year and occupation fixed effects and the Frey/Osborne probability interacted with year (divided by 100).[14] For the full period, the resulting coefficient is .158 (standard error .066). For the later period, it is .388 (standard error .219) and thus remains nontrivial although significant at only the .1 level.

Readers may be concerned that by focusing on workers' measured characteris-

[14] This is asymptotically equivalent to including all the interaction terms in a single equation.

tics, we miss important differences between those who leave threatened or declining occupations and those who stay. To imperfectly address this concern, we use matched CPS samples and limit the sample to workers in the same occupation in both outgoing rotation groups (months four and eight in the sample).

Our estimates suggest that wage growth increased more in occupations threatened by computerization. Using the entire period, we estimate that wage growth increased by .25% per year more in an occupation with a 100% probability of computerization than in one with no probability. When we control for gender, race, marital status, education, and log age, in addition to the year and occupation fixed effects in the baseline, the point estimates rise to .27%. Both estimates are significant at any conventional level. If we limit the sample to 2013-2019, the estimates are .23% and .24% but lose statistical significance.

Table 4: Controls do not eliminate the effect of the Frey/Osborne Probability on Earnings

	2005-2019			2013-2019		
	(1)	(2)	(3)	(4)	(5)	(6)
Probability*year/100	0.324***	0.137	0.171**	0.915***	0.912***	0.618***
	(0.112)	(0.085)	(0.083)	(0.245)	(0.246)	(0.217)
log age		0.352***	0.243***		0.342***	0.243***
		(0.018)	(0.013)		(0.017)	(0.014)
log weekly hours			0.911***			0.907***
			(0.015)			(0.014)
Full-time			0.203***			0.217***
			(0.018)			(0.018)
Demographic controls	N	Y	Y	Y	Y	Y
Observations	1,110,145	1,110,145	1,110,145	527,606	527,606	527,606
Adjusted R-squared	0.401	0.482	0.672	0.396	0.475	0.396
Mean Dependet Variable	5.620	5.620	5.620	5.620	5.620	5.620

Notes: The dependent variable is log weekly earnings. Each estimate controls for occupation and year fixed effects. Demographic controls are: calendar month, state, 6 marital status categories, 25 race groups, gender, and 15 education levels. Robust standard errors clustered by occupation are provided in parentheses.

Recall that the core issue is whether the relative decline in employment among occupations under threat of computerization is driven by demand or supply. The former implies that earnings should fall, while the latter implies the opposite. The weight of the evidence is strongly in favor of supply.

4.5 The Labor Force Got Older

Table 3 also shows that, as predicted by our model, occupations that were more at risk of computerization aged faster than those less at risk. In all three samples using the full period, we estimate that the mean age grew between .044 and .064 more per year in an occupation with a probability of 1 than in one with a probability of 0 of computerization. In all three cases, the coefficient is larger in the second half of the sample period than in the full period, but none of the differences is statistically significant at even the .1 level.

5 Broader Lessons: The Predicament of Current Truckers

We find very mixed evidence regarding the current state of trucking employment. Different sources suggest different conclusions about whether we have entered the anticipatory-dread period, but the clear aging of entrants and those remaining in the occupation suggests we have.

The American Trucking Associations (2021) trade group reports a current truck driver shortage of 'historic' proportions, significant increases in driver pay, and a high average age of current drivers. Our model can explain these movements within the framework of the anticipated arrival of a future shock to demand, which we associate with self-driving trucks. From this perspective, we appear to be in the anticipatory-dread stage of our model.

When commercially viable self-driving trucks will truly be readily available is highly uncertain. It seems to us that they have been "five years away" for a decade. Truck drivers seem to think that their arrival is sufficiently distant that self-driving trucks may be irrelevant for all but the youngest drivers (Shoag et al. 2022). Of course, while not in our model, implicitly, the workers who enter an occupation during the anticipatory-dread state should be those who view the arrival probability as low. Therefore, the views of current drivers may be misleading.

Whether truckers' wages are currently unusually high and their employment low depends on whom we include in the occupation, with whom we compare truckers, and which data source we rely on. If we rely on the Current Population Surveys (CPS), our preferred source because we can track movement in and out of the occupation, we see weak evidence consistent with recent entry into the anticipatory-dread stage, but we do not present it because we would risk misleading readers about the strength of the evidence.

Instead, we focus on and confirm our predictions regarding the relation between age and entry/exit. We identify close unthreatened occupations as those that are a) either the source of at least 5% of entrants or the destination of at least 5% of departures to/from truck driving, b) have average earnings no more than twice that of truck drivers, and c) are in the bottom quartile of the Frey/Osborne risk distribution. This gives the following close occupations: farmers, ranchers, and other agricultural managers; construction managers; food service and lodging managers; chefs and cooks; first-line supervisors of office and administrative support workers; first-line supervisors of production and operating workers.

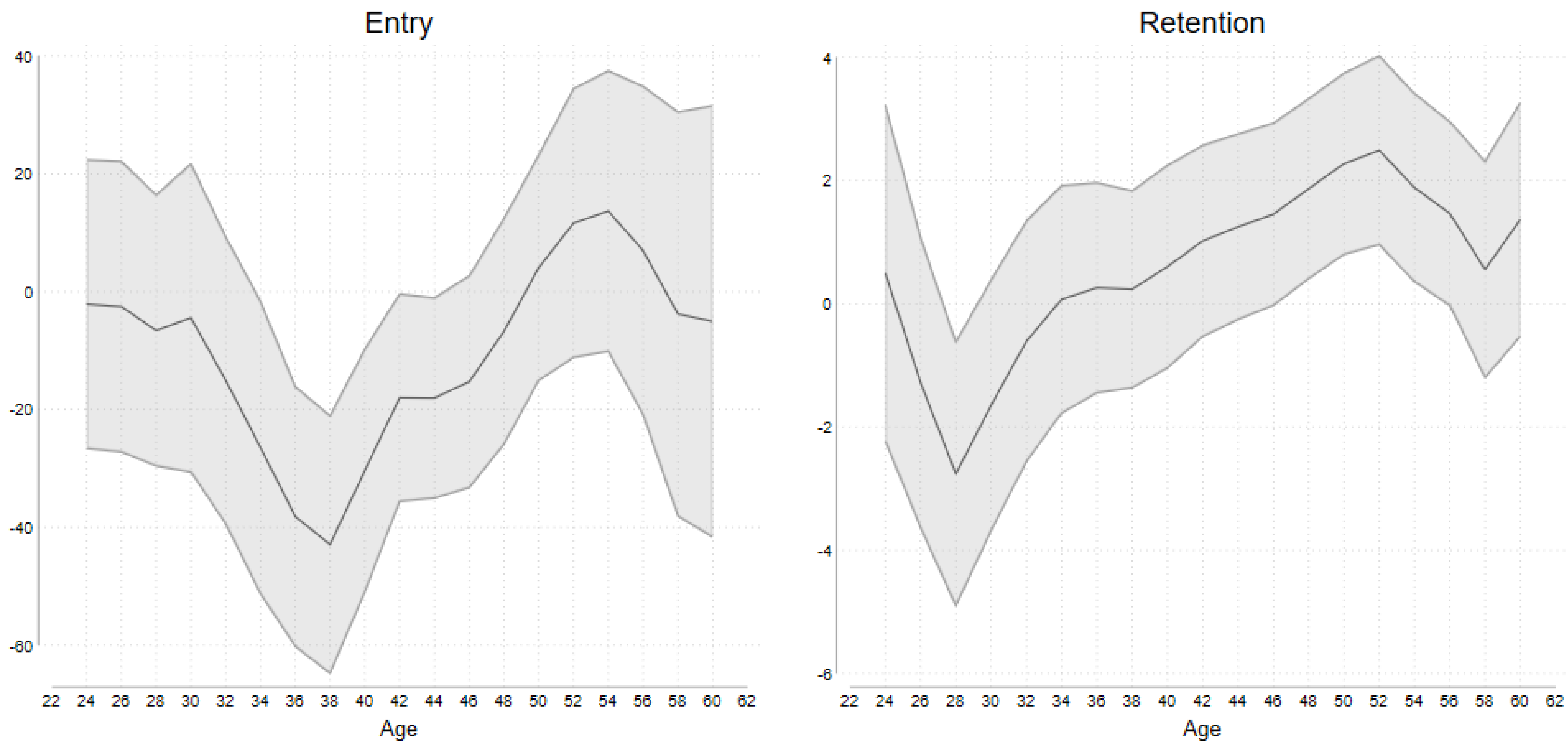
We use the linked CPS to examine entry to and retention in truck driving and the close occupations.[15] We examine how entry and retention in the 2015-18 CPS differs from what we observe in the 2005-06 CPS. Note that the new occupation may be observed first in 2007 or 2019. We restrict the sample to men since 95% of truck drivers are male, and the relation between age and mobility may differ by gender.

Figure 7 shows how entry and retention of truck drivers changed between 2005-06 and 2015-18 relative to entry and exit in the comparison occupations. Contrary to our expectation, entry rates to truck driving and the close occupations changed similarly among workers thirty and younger. In this age group, the relative entry rate of truckers fell only slightly and statistically insignificantly more than in the comparison group. However, we see dramatically and statistically significantly lower entry into truck driving among those aged 30-45 and noticeably higher entry among older workers except those nearing retirement age, few of whom enter truck driving in any event. We also see some evidence of lower retention of younger truck drivers, although the only statistically significant difference is for 28-29 year old workers. Similarly, we see evidence of higher retention of older workers, with statistically significant differences for those aged 46-56. Overall, the results suggest a substantial shifting of entry into and retention in truck driving toward older workers relative to what we observe in the comparison occupations.

While it would be premature to conclude definitively that we have entered a period of anticipatory dread, the aging of entry and retention adds credibility to this conclusion.

[15] Our measures of age composition for workers who entered into and remained in truck driving are generated in a similar way as for teamsters. The main difference is that, here, aligning with the CPS data's structure, the movements are measured based on consecutive surveyed months, taking the former month as the reference month. For example, if a worker is observed to have a non-trucker occupation in January 2005, and the next time he is observed with an occupation is in March 2006, reporting to be a trucker, the worker will be coded as an entrant for January 2005.

Figure 7: Trucker and Comparison Entry/Retention by Age: 2005-06 v. 2015-18



Notes: The figure depicts the age composition of male truckers and a comparison group who either entered or remained in the trucker occupation during consecutive survey months. It captures occupational transitions between the current survey month and the subsequent one when the same individual is re-interviewed. The figure is generated using CPS data. The two months under investigation for occupation changes may not always be consecutive calendar months, aligning with the CPS data's structure. The left panel shows the entry rate into each occupation over consecutive survey months, averaged across 2015-2018, then divided by the corresponding rate in 2005 and 2006 (in percent) and then differenced between truckers and the comparison occupations. The entry rate is defined as the proportion of workers employed in both months who transitioned into the occupation in the following survey month, having been employed in a different occupation in the current month. The right panel shows the retention rate of workers in each set of occupations over consecutive months in 2015-19 relative to consecutive months in 2005 and 2006 (in percent) and then differenced. The retention rate is the number of workers in the occupation in both the current month and the next survey month divided by the number of workers in the occupation who were still in any occupation in the next survey month. The sample is restricted to employed males aged 24-60 who could be matched over consecutive survey months. The shaded areas in the figure represent 95% confidence intervals constructed via bootstrapping, while the central lines connect averages for two-year age bins. For instance, the values associated with age 30 represent calculations for individuals aged 30 and 31, treating them as a single age group.

6 Towards an Understanding of Anticipatory Dread

In sum, our model shows promise for understanding employment and earnings when technological change is on the horizon, a state that seems to be increasingly significant. Foresighted workers are reluctant to enter occupations at risk of obsolescence and receive a wage premium for doing so. Therefore, wages rise, and employment falls while the age distribution shifts right in anticipation of the shock. These predictions are broadly consistent with the available data for teamsters at the dawn of the motor truck and occupations currently threatened by computerization.

Artificial intelligence threatens to be even more disruptive than prior developments in computing and robotics (Hatzius et al. 2023). Therefore, it is vital to understand how workers and markets react when faced with the threat of obsolescence. Our findings show that while technological change is disruptive, so is its expectation. Expert beliefs about technological change are valuable for workforce planning. However, we show that *workers'* beliefs are themselves important to the behavior of labor markets and may be hinted at by changes in age composition.

The effects of beliefs of future disruption in labor markets is currently a gap in the literature. This paper studies aging and wage patterns in markets anticipating shocks. Expectations may affect multiple aspects of the labor market not explored in this paper. Identifying these dimensions and understanding how they manifest themselves during anticipatory dread is crucial to understanding the labor-market consequences of technological change.

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A Appendix: Proofs for Section 2

Before proving our main results, we need a few lemmata. First, we show that for any solution (V_N, V_D, V_A), the steady states o_N^* and o_A^* are global attractors of $F \circ V_N$ and $F \circ V_A$ respectively.

Lemma 1. *For $s \in \{N, A\}$, $o \underset{(>)}{<} o_s^* \implies (F \circ V_s)^2(o) \underset{(<)}{>} o$*

Proof. We show that $o{<}o_s^* \implies (F \circ V_s)^2(o){>}o$; the other case is proven symmetrically. Define $z : [0,1] \to [0,1]$ via $z(o) = (F \circ V)^2(o) - o$ and claim for contradiction that there is an $o' < o^*$ such that $z(o') < 0$. Because the range of F is $[0,1]$, $z(0) \geq 0$. Thus from continuity of z and the intermediate value theorem there must be some $x \in [0, o']$ such that $z(x) = 0$. Which would mean that $(F \circ V)^2(x) = x$. But then for any $n > 0$, $w((F \circ V)^n(x) + (F \circ V)^{n-1}(x))) = w(F(V(x)) + x)$ so that the wage is constant. As the wage is constant, so is the number of entrants $F(V(x))$, and hence x is a steady state. But since $x < o' < o^*$ and since o^* is the unique steady state, we have a contradiction. $\square$

Lemma 2. *For $s \in \{N, A\}$, $o \underset{(>)}{<} o_s^* \implies (F \circ V_s)^2(o) \underset{(>)}{<} o_s^*$*

Proof. We show that $o < o_s^* \implies (F \circ V_s)^2(o) < o_s^*$; the other case is proven symmetrically. We proceed by contradiction again, via two sub-cases.

(Case A.) Suppose $o < o^*$, $F(V(o)) < o^*$ and $(F \circ V)^2(o) > o^*$. From o^* being the steady state, we have that $V(o^*) = (1+\delta)w(2o^*)$. From F strictly increasing and $F(V(o)) < o^*$, we have

$$w(o + F(V(o))) + \delta w(F(V(o)) + (F \circ V)^2(o)) < (1+\delta)w(2o^*). \tag{17}$$

From F strictly increasing and $(F \circ V)^2(o) > o^*$, we have

$$w((F \circ V)^2(o) + F(V(o))) + \delta w((F \circ V)^3(o) + (F \circ V)^2(o)) > (1+\delta)w(2o^*). \tag{18}$$

From Lemma 1 and $F(V(o)) < o^*$ we have that $(F \circ V)^3(o) > F(V(o))$. From this and the strictly decreasing nature of w, we have

$$w((F \circ V)^3(o)) + (F \circ V)^2(o)) < w(F(V(o)) + (F \circ V)^2(o)). \tag{19}$$

Combining this with (18), we obtain

$$w(F(V(o)) + (F \circ V)^2(o)) > w(2o^*). \tag{20}$$

Now, we can use this and (17) to derive

$$w(o + F(V(o))) < w(2o^*). \tag{21}$$

However, ex hypothesi both $o < o^*$ and $F(V(o)) < o^*$, so that given that w is strictly decreasing, we have a contradiction.

(Case B.) Suppose $o < o^*$, $F(V(o)) > o^*$ and $(F \circ V)^2(o) > o^*$. From $F(V(o)) > o^*$, the strictly increasing nature of F, and $V(o^*) = (1+\delta)w(2o^*)$, we have

$$w(o + F(V(o))) + \delta w(F(V(o)) + (F \circ V)^2(o)) > (1+\delta)w(2o^*). \tag{22}$$

From $(F \circ V)^2(o) > o^*$ and similar reasoning, we have

$$w(F(V(o)) + (F \circ V)^2(o)) + \delta w((F \circ V)^2(o) + (F \circ V)^3(o)) > (1+\delta)w(2o^*). \tag{23}$$

As ex hypothesi $F(V(o)) > o^*$ and $(F \circ V)^2(o)) > o^*$, and w is a strictly decreasing function, 23 implies that $(F \circ V)^3(o)) < o^*$. In other words, from the fact that F is strictly increasing,

$$w((F \circ V)^2(o) + (F \circ V)^3(o)) + \delta w((F \circ V)^3(o) + (F \circ V)^4(o)) < (1+\delta)w(2o^*). \tag{24}$$

Now, we use Lemma 1 and $F(V(o)) > o^*$ to obtain

$$(F \circ V)^3(o) < F(V(o)) \tag{25}$$

and similarly Lemma 1 and $(F \circ V)^2(o) > o^*$ to obtain

$$(F \circ V)^4(o) < (F \circ V)^2(o). \tag{26}$$

Thus from the fact that w is strictly decreasing,

$$w((F \circ V)^3(o) + (F \circ V)^4(o)) > w(F(V(o)) + (F \circ V)^2(o)). \tag{27}$$

Now, from combining (23), (24), and (27), we have

$$(1-\delta)w((F \circ V)^2(o) + (F \circ V)^3(o)) < (1-\delta)w(F(V(o)) + (F \circ V)^2(o)) \tag{28}$$

which, from the fact that w is strictly decreasing implies $(F \circ V)^3(o) > F(V(o))$, contradicting (25). $\square$

Lemmata 1 and 2 along with continuity make o_N^*, o_A^* global attractors. Moreover, it is easy to see that $F(V_N(\cdot))$ and $F(V_A(\cdot))$ are injective. As a consequence, $F(V_N(\cdot))$ and $F(V_A(\cdot))$ are strictly decreasing and so are V_N and V_A.

Lemma 3. *For $s \in \{N, A\}$, $o \underset{(>)}{<} o_s^* \implies F(V_s(o)) \underset{(<)}{>} o_s^*$*

Proof. Again, we show that $o<o_s^* \implies F(V_s(o))>o_s^*$ and leave the case with the reversed inequalities to the reader. Suppose $o < o^*$ and $F(V(o)) < o^*$ for contradiction. From Lemma 2, we have $(F \circ V)^2(o) < o^*$. Therefore, from w decreasing, we have

$$V(o) = w(o+F(V(o))+\delta w(F(V(o)+(F\circ V)^2(o)) > (1+\delta)w(2o^*) = V(o^*) \quad (29)$$

and therefore, from F increasing, $F(V(o)) > F(V(o^*)) = o^*$, a contradiction. □

Lemma 4. *In the no-shock and aftermath cases, wages are decreasing as a function of old workers: $w_s(o + F(V_s(o)))$ decreases in o.*

Proof. Suppose for contradiction that $o_1 > o_2$ and $w(o_1 + F(V(o_1))) > w(o_2 + F(V(o_2)))$. Then, from the fact $F \circ V$ is strictly decreasing, $(F \circ V)^n(o_1) < (>)(F \circ V)^n(o_2)$ for n odd (even). From $w(o_1 + F(V(o_1))) > w(o_2 + F(V(o_2)))$ and $F(V(o_1)) < F(V(o_2))$, which implies

$$\begin{aligned} &w(o_1 + F(V(o_1))) + \delta w(F(V(o_1)) + (F \circ V)^2(o_1)) \\ &< w(o_2 + F(V(o_2))) + \delta w(F(V(o_2)) + (F \circ V)^2(o_2)). \end{aligned} \quad (30)$$

Via rearrangement, we have

$$\begin{aligned} &w(o_1 + F(V(o_1))) - w(o_2 + F(V(o_2))) \\ &< \delta[w(F(V(o_2))) + (F \circ V)^2(o_2))) - w(F(V(o_1) + (F \circ V)^2(o_1)))] \end{aligned} \quad (31)$$

which generalizes via an inductive argument to

$$\begin{aligned} &0 < w(o_1 + F(V(o_1))) - w(o_2 + F(V(o_2))) \\ &< \delta^n[w((F \circ V)^n(o_2) + (F \circ V)^{n+1}(o_2)) - w((F \circ V)^n(o_1) + (F \circ V)^{n+1}(o_1))] \end{aligned} \quad (32)$$

for all n odd, which (eventually) contradicts the bounded range of w. □

Lemma 4 plays a role in Propositions 1 and then 2. Proposition 1 is proven by showing that if there were two solutions, wage differences *today* can only be sustained if *future* wage differences explode, contradicting the assumption of bounded wages.[16]

Proposition 1. *The solution* (V_N, V_A, V_D) *is unique.*

Proof. Suppose for contradiction that V_N and $\hat{V}_N$ solve (2), and that wlog $V_N(o) > \hat{V}_N(o)$ for some $o \in [0,1]$. Then by F strictly increasing, $F(V_N(o)) > F(\hat{V}_N(o))$. By w_h strictly decreasing, $w_h(o + F(V_N(o))) < w_h(o + F(\hat{V}_N(o)))$, and therefore to satisfy $V_N(o) > \hat{V}_N(o)$, using (2),

$$\begin{aligned}&w_h(F(V_N(o)) + (F \circ V_N)^2(o)) - w_h(F(\hat{V}_N(o)) + (F \circ \hat{V}_N)^2(o)) > \\ &\frac{1}{\delta}\left[w_h(o + F(\hat{V}_N(o))) - w_h(o + F(V_N(o)))\right] > 0.\end{aligned} \tag{33}$$

From w_h strictly decreasing, then, $F(V_N(o)) + (F \circ V_N)^2(o) < F(\hat{V}_N(o)) + (F \circ \hat{V}_N)^2(o)$. From $V_N(o) > \hat{V}_N(o)$, and F strictly decreasing, we have $(F \circ V_N)^2(o) < (F \circ \hat{V}_N)^2(o)$, and thus $V_N(F(V_N(o))) < \hat{V}_N(F(\hat{V}_N(o)))$. Using (2), we have

$$\begin{aligned}&w_h((F \circ \hat{V}_N)^2(o) + (F \circ \hat{V}_N)^3(o)) - w_h((F \circ V_N)^2(o) + (F \circ V_N)^3(o)) > \\ &\frac{1}{\delta}\left[w_h(F(V_N(o)) + (F \circ V_N)^2(o)) - w_h(F(\hat{V}_N(o)) + (F \circ \hat{V}_N)^2(o))\right] > \\ &\left(\frac{1}{\delta}\right)^2\left[w_h(o + F(\hat{V}_N(o))) - w_h(o + F(V_N(o)))\right] > 0,\end{aligned} \tag{34}$$

where the second inequality follows from (33).

More generally, $w_h((F \circ \hat{V}_N)^{2n}(o) + (F \circ \hat{V}_N)^{2n+1}(o)) - w_h((F \circ V_N)^{2n}(o) + (F \circ V_N)^{2n+1}(o)) > \left(\frac{1}{\delta}\right)^{2n}\left[w_h(o + F(\hat{V}_N(o))) - w_h(o + F(V_N(o)))\right] \to \infty$ which contradicts the bounded domain of w_h. The same argument shows V_A is unique as well. To apply the argument to V_D, we simply make use of Lemma 4 and the uniqueness of V_A to get monotonicity of the wage in the aftermath stage. $\square$

We can now prove Proposition 2:

Proposition 2. $F(V_D(\cdot))$ *has a unique steady state* o_D^*.

Proof. As $F(V_A(\cdot))$ is decreasing, and from Lemma 4 so are aftermath wages $w_l(o + F(V_A(o)))$ as a function of o, the steady-state equation for $F(V_D(\cdot))$,

$$F(V_D(o)) = F((1 + \delta(1 - \lambda))w_h(2o) + \lambda\delta w_l(o + F(V_A(o)))) = o, \tag{35}$$

[16] In fact, wages being bounded below by 0 is sufficient for our results; we only assume an upper bound for convenience.

has a LHS decreasing in o and a RHS increasing in o. Thus, by continuity, it has a unique solution o^*_D. □

Lemma 5. *There are more workers in the anticipatory-dread steady state than in the aftermath steady state: $o^*_D > o^*_A$. Furthermore, the steady-state wage is higher in the anticipatory-dread steady state: $w_h(2o^*_D) > w_l(2o^*_A)$.*

Proof. For the first part, suppose for contradiction $o^*_A > o^*_D$. From (7), (6), and F increasing, this implies

$$(1+\delta(1-\lambda))w_h(2o^*_D) + \lambda\delta w_l(o^*_D + F(V_A(o^*_D))) < (1+\delta)w_l(2o^*_A). \tag{36}$$

From $o^*_A > o^*_D$ and Lemma 4,

$$w_l(2o^*_A) < w_l(o^*_D + F(V_A(o^*_D))). \tag{37}$$

From $o^*_A > o^*_D$ and Lemma 3 we have that

$$F(V_A(o^*_D)) > o^*_A > o^*_D, \tag{38}$$

so that from w_l decreasing we have

$$w_l(F(V_A(o^*_D)) + o^*_D) < w_l(2o^*_D). \tag{39}$$

From $w_h > w_l$ and (37), we have $w_l(2o^*_A) < w_l(2o^*_D) < w_h(2o^*_D)$. Combining this with (37) we arrive at a contradiction to (36).

For the second part of the statement, notice that $o^*_D > o^*_A$ implies $F(V_D(o^*_D)) > F(V_A(o^*_A))$. This and the fact F is strictly decreasing in turn give us

$$(1+(1-\lambda)\delta)w_h(o^*_D) + \lambda\delta w_l(o^*_D + F(V_A(o^*_D))) > (1+\delta)w_l(2o^*_A). \tag{40}$$

From $o^*_D > o^*_A$ and Lemma 4, $w_l(o^*_D + F(V_D(o^*))) < w_l(2o^*_A)$. From this and (40), we have that $w^*_h(2o^*_D) > w_l(2o^*_A)$. □

Lemma 6. $w_h(2o^*_D) > w_l(o^*_D + F(V_A(o^*_D)))$.

Proof. From Lemma 5 $o^*_D > o^*_A$; from Lemma 4 and this, $w_l(o^*_D + F(V_A(o^*_D))) < w(2o^*_A)$. From the second part of Lemma 5, $w^*_h(2o^*_D) > w_l(2o^*_A)$, and thus $w_h(2o^*_D) > w_l(o^*_D + F(V_A(o^*_D)))$. □

We can now use Lemma 6 to prove Proposition 3:

Proposition 3. *The steady-state numbers of old workers satisfy* $o_N^* > o_D^* > o_A^*$ *and* $w_h(2o_D^*) > w_h(2o_N^*) > w_l(2o_A^*)$.

Proof. We begin with wages, and proceed separately for each of the two inequalities. First, from F increasing, $w_h > w_l$, w_h and w_l strictly decreasing, we have that $w_l(2o_A^*) < w_h(2o_N^*)$. Now suppose for contradiction that $w_h(2o_D^*) \leq w_h(2o_N^*)$. Then, $o_D^* \geq o_N^*$ from the fact that w_h is strictly decreasing. Using (5) and (6), as well as the fact F is strictly increasing, we deduce

$$(1+\delta)w_h(2o_N^*) \leq (1+\delta(1-\lambda))w_h(2o_D^*)+\lambda\delta w_l(o_D^*+F(V_D(o_D^*))) < (1+\delta)w_h(2o_D^*), \tag{41}$$

where the last bit follows from Lemma 6's implication that $w_h(2o_D^*) > w_l(o_D^* + F(V_D(o_D^*)))$, yielding a contradiction. Thus $w_h(2o_D^*) > w_h(2o_N^*) > w_l(2o_A^*)$.

To show that $o_N^* > o_D^* > o_A^*$, we have but to use the monotonicity of w_h and $w_h(2o_D^*) > w_h(2o_N^*)$ for the first inequality, and Lemma 5 for the second one. $\square$

Proposition 4. $w_l(2o_A^*) > w_l(o_D^* + F(V_A(o_D^*)))$.

Proof. From Lemma 4, $w_l(o+F(V_A(o)))$ is decreasing in o, so that from w_l decreasing, $o+F(V_A(o))$ is increasing in o. From Proposition 3, $o_A^* < o_D^*$. Combining these facts, $o_D^* + F(V_A(o_D^*)) > 2o_A^*$. Thus, from w_l decreasing, $w_l(o_D^* + F(V_A(o_D^*))) < w_l(2o_A^*)$. $\square$

Proposition 5. *There is some* $\underline{\pi} > 0$ *such that* $\pi \in (\underline{\pi}, 1)$ *implies that* $o_D^* > o_N^*$.

Proof. Having noticed that $o_D^* = o_N^*$ when $\pi = 1$, we proceed by showing that the derivative of o_D^* is negative at $\pi = 1$. The total number of old widgeters is, in general,

$$o_t = (1-\pi)y_{t-1} + \pi F((1+\delta)w_t)$$

In steady state, we can omit the time subscripts:

$$o^* = (1-\pi)y^* + \pi F((1+\delta)w^*).$$

Differentiating with respect to π gives us:

$$\frac{do^*}{d\pi} = [F((1+\delta)w^*) - y^*] + (1-\pi)\frac{dy^*}{d\pi} + \pi(1+\delta)F'\frac{dw^*}{d\pi}.$$

Evaluating at $\pi = 1$, and using that

$$F((1+\delta)w^*) - y^* = 0,$$

as there are an equal number of old and young when $\pi = 1$, we have

$$\frac{do^*}{d\pi} = (1+\delta)F'\frac{dw^*}{d\pi}.$$

As F is strictly increasing and hence $F' > 0$, to prove the proposition it remains to show that $\frac{dw^*}{d\pi} < 0$. This cannot be positive, because wages must be weakly decreasing in labour mobility. However, it could still be that wages are non-increasing, but the derivative is zero at $\pi = 1$. We now show this cannot be the case. The total number of widgeters is

$$(1-\pi)y_{t-1} + \pi F((1+\delta)w_t) + y_t.$$

In steady state, this reduces to

$$\pi[F((1+\delta)w^*) - y^*] + 2y^*.$$

Differentiating with respect to π and plugging in $y^* = F\left((1+\delta)\frac{w+\delta(1-\pi)E[w_{t+1}]}{1+\delta(1-\pi)}\right)$, we get

$$F'(1+\delta)\left[2\frac{dw^*}{d\pi} + \delta(w^* - E[w_{t+1}])\right].$$

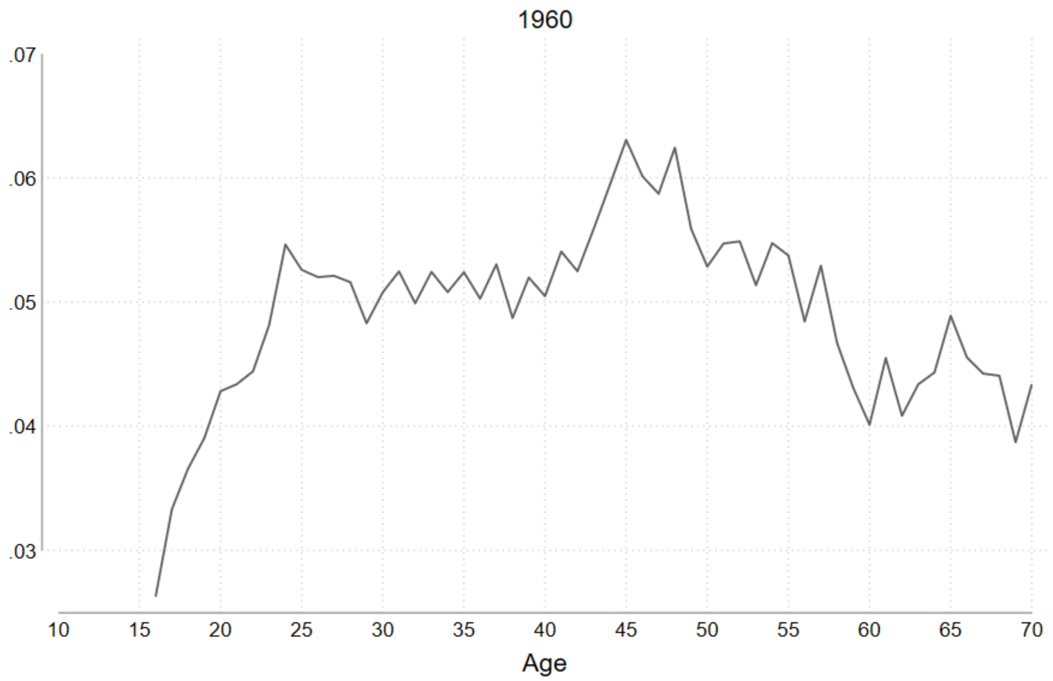
As the wage if the shock hits is lower than in the anticipatory-dread steady state (from Propositions 3 and 4), $w^* - E[w_{t+1}] > 0$. Thus, assuming for contradiction $\frac{dw^*}{d\pi} \geq 0$, the total number of widgeters in the anticipatory-dread steady state would be strictly increasing in π, which would in turn imply $\frac{dw^*}{d\pi} < 0$ (as w is a strictly decreasing function of the number of workers), a contradiction. □

B Appendix: Supplementary Figures and Tables

Figure B.1: Teamster Age Composition: 1900-1930

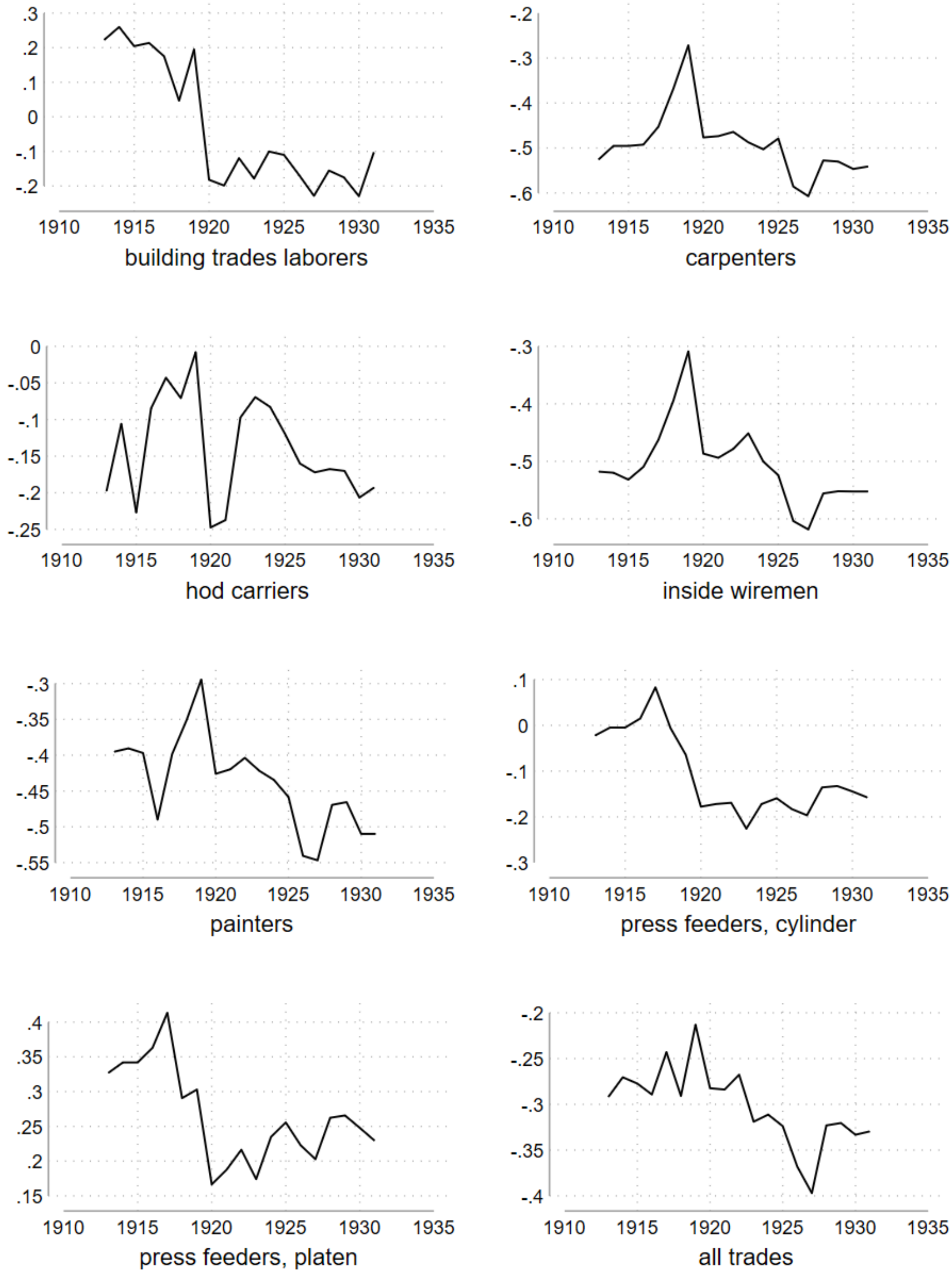
Notes: The figure shows the teamster share in employed males by age. We restrict ages to 16-70. The lines are smoothed using 5-year moving averages.

Figure B.2: Teamster Age Composition: 1960



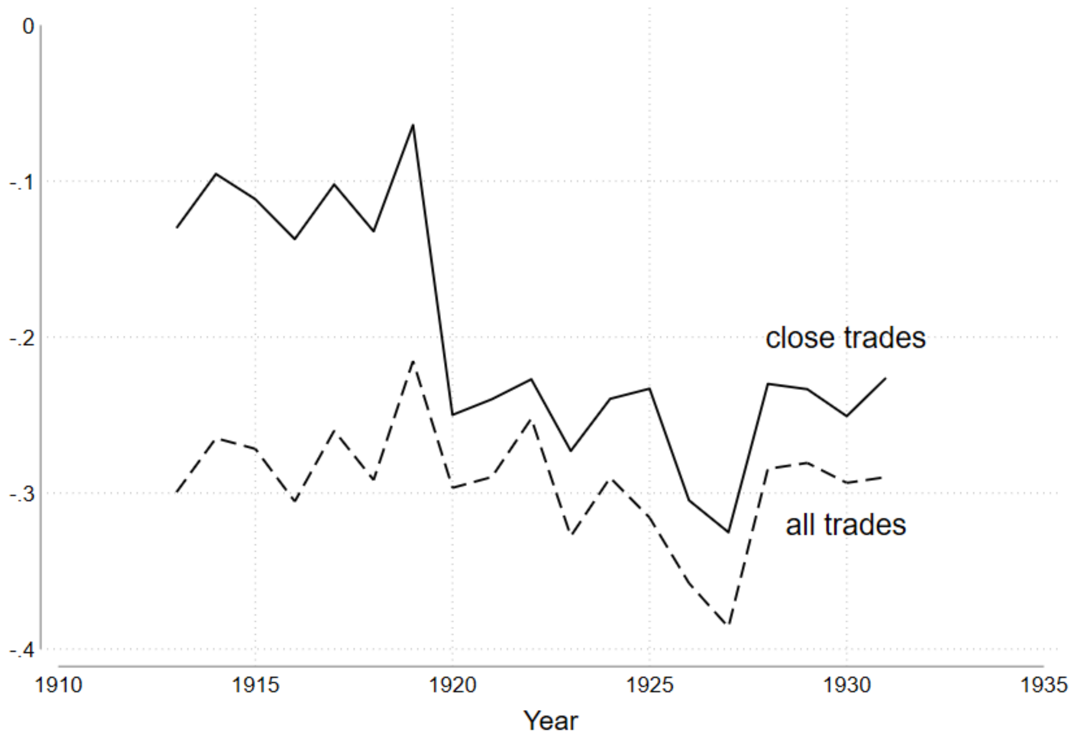
Notes : The figure shows the teamster share in employed males by age generated using the IPUMS census sample 1960 (5%). The 1960 census sample does not have the variable *occstr*, so we have to use only *occ1950* to identify teamsters. We restrict ages to 16-70. The lines are smoothed using 5-year moving averages.

Figure B.3: $\ln w_{\text{teamster}} - \ln w_{\text{other}}$



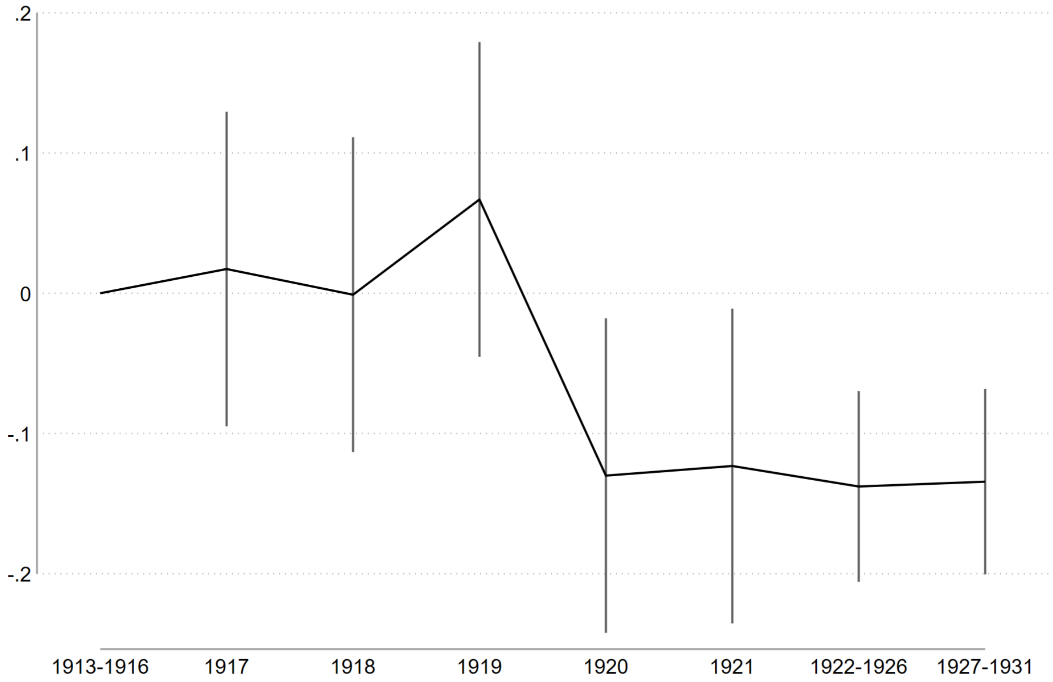
Notes : The figures show wage differences between teamsters and other occupations. Wage differences are measured by subtracting the log weekly wages of close trades or all trades from the log weekly wages of teamsters. The differences are then weighted by cities male labor force to get an average. Aside from "all trades" in the last panel, other occupations are used as comparisons because they are close occupations to teamsters. Occupations are used for comparison if 1) their wages are close to teamsters in 1896-1900, 2) they have data for at least 4 cities of interest, and 3) they have available data in 1913-1931. For the last panel, "all trades" is the average of all the selected trades and cities covered in each BLS bulletin. The sets of trades and cities are inconsistent over time for "all trades".

Figure B.4: Wage differences between teamsters and other occupations (averages): Excluding Chicago



Notes: The figure shows wage differences between teamsters and the average wages of close trades or all trades. Chicago is dropped from the analysis to avoid potential disruption from their strong union. Wage differences are measured by subtracting the log weekly wage of close trades or all trades from the log weekly wage of teamsters. "Close trades" is the simple average of the log wage of all the close trades: building trade laborers, carpenters, hod carriers, inside wiremen, painters in building trades, and the two types of press feeders. These occupations are used as comparisons because 1) their wages are close to teamsters in 1896-1900, 2) they have data for at least 4 cities of interest, and 3) they have available data in 1913-1931. "All trades" is the average of all the selected trades and cities covered in each BLS bulletin. The sets of trades and cities are inconsistent over time for "all trades".

Figure B.5: Wage differences between teamsters and other occupations: Excluding Chicago



Notes : The Figure shows the estimation results using Equation (16). Chicago is dropped from the analysis to avoid potential disruption from their strong union. Bars reflect 95% confidence intervals. The regression is weighted by the cities' male labor force.

Table B.1: Primary Destination Occupations of Workers Leaving Employment as Laborers (nec)

	Laborer (nec)	Farmers owners & tenants	Truck/Tractor Drivers	Managers, Officials Proprietors (nec)	N
1910-1920	-				
26-35	-	18.51	1.67	4.56	133,773
36-45	-	24.45	1.04	5.99	90,977
46-55	-	26.07	0.71	6.36	63,519
56-65	-	26.78	0.47	5.56	31,047
1920-1930					
26-35	-	11.43	5.55	5.45	137,693
36-45	-	16.61	3.13	7.27	102,393
46-55	-	19.80	1.78	7.51	67,765
56-65	-	22.88	0.90	7.03	40,011

Notes: nec = not elsewhere classified.

Source: Authors' calculations based on pairwise matched Census data.