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Technical Change and Superstar Effects: Evidence from the Rollout of Television[†]

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Technical change that extends market scale can generate winner-take-all dynamics, with large income growth among top earners. I test this "superstar model" in the entertainer labor market, where the historic rollout of television creates a natural experiment in scale-related technological change. The resulting inequality changes are consistent with superstar theory: the launch of a local TV station skews the entertainer wage distribution sharply to the right, with the biggest impact at the very top of the distribution, while negatively impacting workers below the star level. The findings provide evidence of superstar effects and distinguish such effects from popular alternative models. (*JEL* D31, J31, J44, L82, L88, O33)

In a celebrated 1981 article, Sherwin Rosen argues that technical change can amplify inequality at the top of the wage distribution and generate extremely well-paid "superstar" earners. The driving force of such superstar effects is technological change that facilitates an increase in market scale. Rosen concludes that these technologies enable "many of the top practitioners to operate at a national or even international scale … [and lead to] increasing concentration of income at the top" (Rosen 1981, 856).[1] Superstar theory has been enormously influential and has been used as the basis for modeling income inequality in a number of important settings.[2] Even so, there is little in the way of causal evidence for the theory, and

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[1] Early versions of the superstar theory appear in Tinbergen (1956) and Sattinger (1975, 1979).

[2] See, for example, Terviö (2008); Gabaix and Landier (2008); and Gabaix, Landier, and Sauvagnat (2014) for CEOs; Garicano and Hubbard (2009) for lawyers; Kaplan and Rauh (2010) and Célérier and Vallée (2019) for finance professionals; Krueger (2005, 2019) for entertainers; and Cook and Frank (1995) and Kaplan and Rauh (2013) for reviews in multiple sectors.

Rosen's headline prediction about the impact of scale-related technologies on the earnings distribution remains to the best of my knowledge untested.[3]

This paper develops a test of the superstar model and uses a natural experiment to implement it. The paper studies the entertainment sector—arguably the most prominent field in which superstar effects are thought to arise—during the historic rollout of television.[4] Before the launch of television in the middle of the twentieth century, successful entertainers typically had live audiences of a few hundred individuals; after the launch of television, audiences were an order of magnitude larger. In line with predicted superstar effects, I find that this shift resulted in disproportionate income gains for top entertainers, with much smaller gains for second-tier stars and serious adverse effects for average talents.

The test uses a set of predictions of the superstar model that were at the heart of Rosen's original article. I follow Rosen in presenting a closed-economy model. In the empirical application one might expect additional effects through trade that are not modeled here. Existing theoretical work focuses on cross-sectional predictions of superstar effects and compares the dispersion of talent to the dispersion of incomes. Unfortunately, though, it is challenging to test cross-sectional predictions because such tests require a credible cardinal measure of talent. Instead, I use the canonical model to derive predictions that focus on *changes* to inequality that can be tested without data on the talent distribution. These changes were the focus of Rosen's original argument and occur during periods of technical change, specifically when "scale-related technical change" (SRTC) relaxes diseconomies of scale, thereby making large-scale production feasible.[5]

The model predicts that SRTC magnifies superstar effects and produces inequality changes that are different from other classic models of technical change. During SRTC, the most talented workers in the profession (the "superstars") attract an increased share of customers at the expense of lower-ranked talents. This process creates a few winners, with very high incomes, while reducing the total number of jobs. The right tail of the income distribution grows, and incomes become concentrated at the top, while employment and returns of lower-level talents decline.

The US government deployment plan of early television stations provides clean variation for a major SRTC, which facilitates a test of superstar model predictions. Entertainer audiences expanded via TV, and shows eventually reached a national audience. However, this transformation took place in stages.[6] Shows on early TV stations were broadcast via airwaves to the local population, and in this pioneering period technological constraints required TV shows to be filmed near the broadcast

[3] A comparable state of affairs existed during the early development of theories and evidence concerning labor market effects of skill-biased technical change more broadly. Several observers, including Card and DiNardo (2002) and Lemieux (2006), stressed the need for clean identification to test theories of skill-biased technical change. Several subsequent studies indeed leveraged exogenous variation to implement such tests—for example, Bartel, Ichniowski, and Shaw (2007); Akerman, Gaarder, and Mogstad (2015); Michaels and Graetz (2018); and Feigenbaum and Gross (2020).

[4] Many classic studies of superstar effects motivate their analysis with examples from the entertainment industry (see, e.g., Rosen 1981; Cook and Frank 1995; Krueger 2019).

[5] Superstar effects also require imperfect substitutability of talent, as is typically the case in the entertainment sector.

[6] Mass media (e.g., radio, newspapers, and cinema) predates television and could reach a national audience. Television made additional entertainment formats scalable, and the local variation largely unfolds orthogonal to established media formats.

antennas. As a result, filming occurred simultaneously in multiple local labor markets, providing entertainers with a bigger platform in locations where stations were launched. Pioneering work on the US television rollout in Gentzkow (2006) and Gentzkow and Shapiro (2008) used the staggered rollout process and regulatory interruptions as a natural experiment to study impacts on television viewers. Building on this work, I study the effect of television on workers in the entertainment sector. The study uses a difference-in-difference (DID) analysis across local labor markets during the staggered TV rollout and leverages government rollout rules that led to quasi-random variation in the timing of TV launches.

The launch of a TV station skewed the entertainer income distribution to the right, with most of the skew happening in the very top tail. The fraction of entertainers with incomes that reach the top 1 percent of the US wage distribution doubled, with smaller increases at slightly lower income levels. Further down in the distribution, such gains disappear and lower-ranked talents lost out. The share of entertainers with midpaid jobs declined, and the total employment of entertainers contracted by approximately 13 percent. In short, SRTC moved the entertainment industry toward a winner-take-all extreme, as predicted by superstar theory.

Two additional sources of variation help to strengthen the identification strategy. First, I use an unplanned interruption of the television deployment process. During the interruption, a group of places that were next in line for television had their permits blocked. Newly collected data on pending regulatory decisions allows me to track affected places.[7] Such places show no evidence of spurious shocks, and results from placebo tests support the assumption that the television deployment was exogenous to local demand conditions. Second, I exploit the staggered launch of TV stations combined with a subsequent decline of *local* filming. The advent of TV recording should remove local superstar effects of local stations, as recordings can be broadcast nationally. I confirm that the local treatment effect disappears after the emergence of TV recordings.

My study contributes to the literature on the impact of technical change on the labor market. Influential work has analyzed effects on the skill premium (Katz and Murphy 1992; Autor, Levy, and Murnane 2003; Acemoglu and Autor 2011; Autor 2014; Autor, Goldin, and Katz 2020) and on routine occupations (Autor, Katz, and Kearney 2008; Acemoglu and Autor 2011; Autor and Dorn 2013), and subsequent work has tested and confirmed these theories in natural experiments (see, e.g., Bartel, Ichniowski, and Shaw 2007; Akerman, Gaarder, and Mogstad 2015; Michaels and Graetz 2018; Feigenbaum and Gross 2020). My work is most similar to these latter studies; my distinctive contribution is to use a natural experiment to test whether SRTC has the effects predicted by superstar theory.

I. Superstar Effects and SRTC

The canonical superstar model, following Gabaix and Landier (2008) and Terviö (2008), features workers (actors) with heterogeneous talent (t) and employers (theaters) of varying size (s) and a production function where t and s are complements

[7] Previous studies indirectly use this interruption period but lacked the data to identify specific locations held up by the interruption.

$\left(\frac{\partial Y}{\partial s \partial t} > 0\right)$. For simplicity, assume that t and s are Pareto distributed with shape parameters α and β, respectively. The share of individuals with talent bigger than t, denoted by p_t, is therefore given by the CDF's complement $p_t = t^{-1/\beta}$ and similarly for s, $p_s = s^{-1/\alpha}$.

Turning to the revenue of a theater, I follow the literature on superstar effects and assume that each theater hires only one entertainer. The revenue of a theatre of size s that hires worker with talent t is $Y(s,t) = \pi(st)^{1/\phi}$, with output prices π and ϕ the degree of returns to scale in production, which determines the cost of large-scale production.[8] SRTC changes parameter ϕ.

We can use this setup to characterize the equilibrium wage distribution in this superstar economy. The share of workers with income above ω, denoted by p_ω, is (for derivations, see the online Appendix, Section B1):

$$\ln(p_\omega) = \gamma_0 - \gamma_1^\omega \phi, \tag{1}$$

with $\gamma_0 = \frac{\phi}{\alpha + \beta}\ln\left(\frac{\beta\pi}{\alpha+\beta}\right)$, and $\gamma_1^\omega \equiv \frac{\ln(\omega)}{(\alpha+\beta)}$ functions of model parameters.

To formalize Rosen's notion of superstar effects, consider SRTC that expands production scalability by decreasing ϕ. We can use equation (1) to evaluate the impact of such technical change on the wage distribution. Both terms of equation (1) are affected by ϕ. The first term affects all workers equally and captures the general change in marginal cost and marginal revenues. The gains, by contrast, are unequally distributed. These unequal effects are captured by γ_1^ω, which varies with the wage level ω. In particular, γ_1^ω is bigger for larger ω and SRTC thus generates larger gains at the top of the distribution. The impact of such SRTC on inequality can be summarized in testable predictions about the income distribution (for proofs, see online Appendix Section B2):

PROPOSITION 1: *In the superstar economy*, *SRTC leads to*

(*i*) top wage growth: for sufficiently high income k, SRTC increases the share of workers above this extreme income level: $\Delta \ln(p_\omega)|_{\omega>k} > 0$;

(*ii*) fractal inequality: the effect of SRTC on the share of workers with income greater than ω (p_ω) is larger at higher income levels: $\Delta \ln(p_\omega) > \Delta \ln(p_{\omega'})$ if $\omega > \omega'$;

(*iii*) adverse effects for lesser talents: employment at midpay levels declines; and

(*iv*) employment loss: for a given outside option w^{res} and corresponding participation threshold $\bar{p}$, SRTC increases the participation threshold $\bar{p}$; that is, $\partial \bar{p}/\partial \phi < 0$.

[8] The results hold for broader functional form assumptions, as highlighted by Rosen (1981); Gabaix and Landier (2008); and Terviö (2008).

The impact of SRTC varies by income level and moves the labor market toward a winner-take-all setting. In Proposition 1, (i) and (ii) highlight that SRTC disproportionally benefits the very top tail of the distribution—the superstars. Specifically, SRTC produces an increase in the share of workers with extremely high incomes ((i)) and widens the gap between the very top tail and slightly lower-ranked talents ((ii)). As stars serve a larger share of the overall market, incomes for lower-ranked workers decline and the share of midpaid jobs decreases ((iii)). Finally, at the bottom end of the distribution, additional low-paid jobs emerge and, in partial equilibrium with exit, workers will leave the industry ((iv)).[9] These predictions are summarized in Figure 1, panel A, while Figure 1, panel B shows the corresponding empirical results that will be discussed below. At the top end of the distribution, the figure looks like an upward pointing hockey stick as the right tail of the distribution grows at the fastest rate (red markers indicate narrower wage ranges). By contrast, the share of workers with midpaid jobs is reduced and more workers are in low-paid positions.

Finally, note that this benchmark superstar model is a closed-economy model. There could be offsetting "import effects" in an open economy, resulting in declining local wages and employment when content from other communities replaces local talent. Such imports may generate employment loss, even in the absence of local superstar effects, and dampen any wage growth of superstars. This makes it harder to detect superstar effects, and we need sufficiently strong superstar effects to detect the closed-economy predictions in an open-economy setting.

Superstar effects differ from alternative models of technical change in several ways. Canonical skill-biased technical change (SBTC), for example, features only two skill groups and thus produces little top-income dispersion. Even extensions to SBTC models with greater type heterogeneity will still struggle to generate the fractal top-income inequality described above. To replicate fractal inequality with SBTC, we would need to introduce more groups of workers that are imperfect substitutes. This is in principle feasible by taking the number of skill groups to infinity. Such an approach, however, is unattractive, as it introduces infinitely many parameters and makes the model impossible to falsify. The superstar economy instead provides a parsimonious and thus falsifiable model of income inequality. A second challenge for models with labor augmenting technical change is to generate real wage *and* employment losses (Caselli and Manning 2019). The superstar framework produces such losses naturally, as shown by (iii) and (iv) in Proposition 1.

An alternative class of models has introduced task-specific technical change (for a summary, see Acemoglu and Autor 2011). Such models have similarities to the superstar framework in that the latter also uses an assignment process to assign workers to tasks (or stages in our case). The task framework can produce real wage declines in response to labor augmenting technical progress by shifting workers into other tasks and increasing the supply of workers to such tasks. When it comes to top-income dispersion, task models face similar limitations to SBTC: workers of equal skills are perfect substitutes, and wage dispersion thus arises across skill groups only. We can generate a task model that is near isomorphic to a superstar model by letting the number of tasks and skill groups approach infinity.

[9] The extent to which the low-paid sector grows, or exit occurs, depends on parameter assumptions.

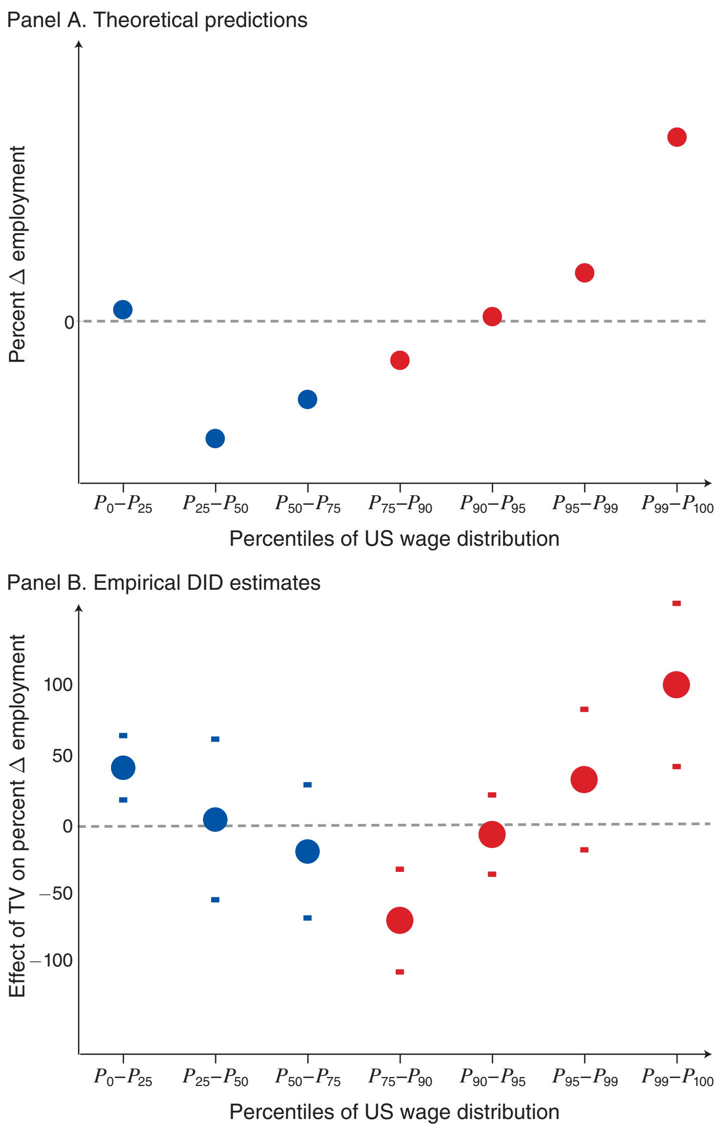

FIGURE 1. SRTC EFFECT: ENTERTAINER EMPLOYMENT AT DIFFERENT WAGE LEVELS

Notes: The figure shows the impact of SRTC on employment growth at different wage levels. Blue markers show effects at the bottom three quartiles and red markers at narrower ranges at the top. Panel A shows the theoretical predictions of SRTC, derived by differentiating equation (1) and parametrizing the result for a stylized shock that changes the scale parameter by factor 1.3 and the intercept by 0.2. The wage levels that correspond to P_{xx} are chosen from the US wage distribution to simplify comparison with the empirical results. Wages outside the range of previous support are grouped with the final bins to avoid undefined growth rates. Panel B shows empirical results from estimating equation (2), restricting $\beta_t = 0$ after the videotape launch in 1956. Each dot is a β coefficient from a separate regression with the outcome variable shown on the x-axis: P_0–P_{25}, for instance, refers to the share of entertainers with income between the zeroth and twenty-fifth percentiles of the US wage distribution. Dashes indicate 95 percent confidence intervals.

Sources: US censuses 1940–1970

A remaining difference is how the two models conceptualize technical change. The task model studies the impact of factor augmenting shocks. To produce fractal inequality with such shocks, one has to assume that the technological shock is fractal itself, in the sense that technology boosts productivity most for the highest-productivity workers. And while it is thus possible to generate fractal inequality, we would essentially assume the conclusion that we generate. In the superstar framework, technical change (SRTC) affects a different parameter (the scale parameter), and the effect on labor demand at different skill levels arises endogenously, producing fractal inequality.

II. Empirical Test of Superstar Effects

I test the predictions of the superstar model by analyzing changes in the labor market for entertainers during the rollout of television. Television is a canonical case of SRTC, sharply expanding audience reach for entertainers. At the aggregate level, inequality in entertainment grew in line with superstar effects. Between 1940 and 1970, the entertainer wage distribution became more right skewed and midpaid positions were reduced (Figure 2, panel A). At the same time, employment growth among entertainers lagged behind the rest of the leisure industry (Figure 2, panel B).

To estimate the causal impact of television, I exploit several features of the rollout process. First, technological and regulatory constraints largely confined pioneering TV stations to film live and locally to the broadcast antenna. And while some shows were relayed nationally, early transmission technologies led to poor image quality, which meant that such nonlocal shows were only used sparingly. The launch of an antenna thus produces SRTC for entertainers in the local area. The rollout of TV stations happened through a government deployment plan that was based on predetermined local characteristics of the location (see Gentzkow 2006; Gentzkow and Shapiro 2008). I digitize the priority rankings, alongside the rules that went into designing them from *TV Digest* reports (for additional information on the data, see Section C1 in the online Appendix).

A second source of variation is an unplanned interruption of the rollout in 1948. Several stations narrowly lost out on launches when the FCC discovered an error in their signal propagation model. This model was used to delineate interference-free signal catchment areas, but the error implied that signal interference occurred between neighboring stations. To avoid a worsening of the situation, the FCC put all licensing on hold and ordered a review of the model. I digitize information on these blocked locations and use them for placebo tests in the analysis. The deployment resumed only four years later after extensive fieldwork.

Finally, we also observe the decline of local TV filming. The invention of the videotape recorder in 1956 made local filming obsolete and shifted filming to the national level. We can use this period to test whether local stations stop generating local superstars. During this videotape era, we have to account for the emergence of national filming hubs, and regressions will include fixed effects for hubs in the postvideotape period. To avoid a potential endogenous control issue, I do not control for filming hubs directly but use a proxy for comparative advantages of a location as a filming hub. These proxies are based on a location's fixed characteristics, such as sunshine hours and landscapes, that largely drove location decisions. I

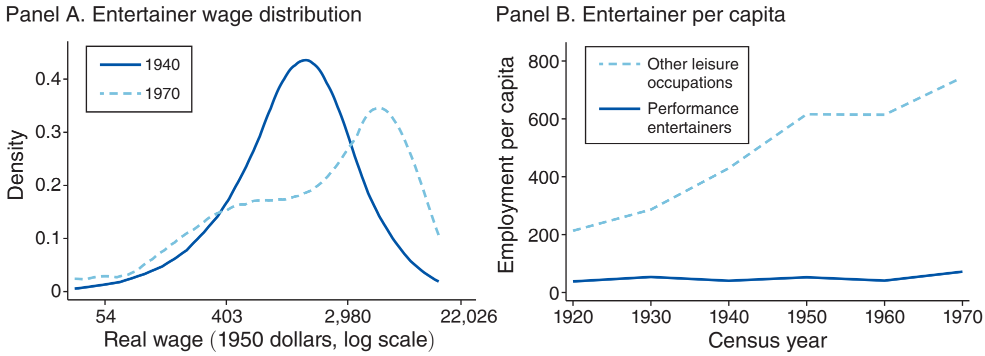

FIGURE 2. CHANGE IN ENTERTAINMENT 1940–1970

Notes: Panel A shows the entertainment log real wage distribution in 1940 and 1970 from the lower 48 states. Dollar values are in 1950 US dollars. Density is estimated using the Epanechnikov smoothing kernel with a bandwidth of 0.4 and census sample weights. Common top code applied at $85,000. Panel B shows employment per 100,000 inhabitants of performance entertainers (defined in the text) and other leisure-related occupations (bars and restaurants and "other entertainment occupations"). Mean employment per capita for performance entertainers is 49 and for other leisure occupations 468.

Sources: US population censuses

quantify such predetermined factors using the share of movies filmed in the local labor market in 1920.

The baseline analysis uses a DID design that compares local labor markets during the launch and subsequent decline of local filming. The analysis covers five occupations that commonly appeared on television (actors, athletes, dancers, musicians, and entertainers not elsewhere classified) and analyses the 722 US mainland local labor markets defined by Autor and Dorn (2013). Data on local entertainers come from the US decennial population census and span the decades 1940–1970, while data on television exposure comes from hand-collected data on the location of television stations during the rollout (for additional information on the data, see section C1 in the online Appendix). The DID estimation equation is

$$Y_{mot} = \alpha_m + \delta_{ot} + \gamma \mathbf{X}_{mt} + \beta_t TV_{mt} + \epsilon_{mot}, \tag{2}$$

where Y_{mot} measures labor market outcomes in labor market (m), year (t), occupation (o) (e.g., the share of entertainers in the top 1 percent of the US wage distribution), α_m and δ_{ot} are labor market and occupation-year fixed effects, and $\mathbf{X}_{mt}$ is a vector of control variables that includes the control for filming hubs of the postvideotape period. The treatment variable, TV_{mt}, is the number of local TV stations (for results with a TV dummy, see Section C3 in the online Appendix). β_t captures the effect of local television stations, and this effect is allowed to change with the invention of the videotape in 1956. The standard errors ϵ_{mot} are clustered at the local labor market level so that running the analysis at the disaggregated level will not artificially lower standard errors. The full sample includes 722 local labor markets, five occupation groups, and four census years (two for athletes, as the category is discontinued) and hence uses 13,718 observations and 722 clusters.

The first set of outcomes tracks changes in the entertainer earnings distribution. Following equation (1), I compute p_ω—the share of entertainers that reach income level ω—in each local labor market. I process the data in two ways. First, I deflate wage thresholds ω to make comparisons over time easier. The baseline deflator is the national wage growth at the corresponding wage percentile (results are robust to alternative deflators). With this adjustment, the outcome variable measures the rank position of entertainers in the US wage distribution of all workers. For example, a measure of extremely high incomes in entertainment is the share of local entertainers that reach the top 1 percent of the national US wage distribution.[10] A potential issue with these shares is that fluctuations in the denominator can generate spurious effects. To prevent this, I fix the denominator. The baseline results use the average employment count across labor markets as the denominator.[11] The results are, however, robust to alternative normalizations or using no such normalization (for robustness checks, see Section C3 in the online Appendix).

The television variation has several advantages and addresses three "endogeneity challenges" that have made it difficult to obtain causal estimates of the effect of technological change on inequality. First, the government deployment process breaks the direct link between local economic conditions and television launches and avoids the simultaneity problem that arises from ordinary, endogenous technology adoption.[12] Second, television is a SRTC that affects one market only—the provision of in-home broadcasting—and unlike other SRTCs (such as the internet) has little impact on other markets, which makes it a particularly clean case of SRTC. Finally, the rich variation from blocked stations and the timing of launches and removal enables us to distinguish the effect of television from simultaneous economy-wide trends (such as deregulation, shifting norms, and so forth).

III. Empirical Results

A. *Changes in the Wage Distribution*

As a starting point, I estimate the DID equation (2) to test the superstar economy predictions outlined in Proposition 1. In that proposition, (i) states that the share of entertainers at extreme income levels increases. An example of an entertainer who became famous through the launch of a local TV station is Korla Pandit, the star of *Korla Pandit's Adventures in Music*, which aired multiple days a week on the Los Angeles TV station KTLA. Korla was an eccentric organist who pretended to be Indian and performed exotic music in a light-blue, jewelry-decorated turban. His show was a local favorite, and he was voted "the local personality most deserving of national recognition" in a poll of the local *TV Guide* magazine.[13] To test for

[10] Wages in the US census are top coded, and the wage top code bites above the ninety-ninth percentile of the US distribution. We can thus identify all workers in the top 1 percent but cannot analyze more granular fractiles.

[11] To interpret the estimates as percentage point changes, I normalize by the average number of entertainers in *treated* labor markets.

[12] For a discussion of endogenous technical change, see Acemoglu (1998); for historical evidence, see Beaudry, Doms, and Lewis (2010).

[13] The life story of Korla Pandit was turned into a documentary film titled *Korla*.

such effects formally, I study the impact of television on the share of entertainers among the top 1 percent highest-paid Americans by estimating equation (2) with a single time-invariant $\beta = \beta_{t<1956}$ that captures the average effect of stations before the launch of the videotape. The estimate and corresponding standard errors are shown on the far right of Figure 1, panel B. A local TV station increases the share of extremely high-paid entertainers by 4 percentage points on a baseline of 4 percentage points. A local TV station thus roughly doubles the share of local entertainers at these extreme income levels.

I next repeat the DID estimation for slightly lower income, between the ninetieth and ninety-ninth percentiles. Figure 1, panel B shows the coefficient next to the results of the previous regression. Strikingly, the effect of television on this income range is already substantially weaker. The point estimate shows a 50 percent increase in employment of entertainers in this range, an effect that is only half as big as the impact at the very top. Indeed, we cannot rule out that television had no effects on employment growth between the ninetieth and ninety-ninth percentiles. The polarization of the income distribution thus occurs predominantly in the very top tail. Television disproportionally benefited a small group of entertainers with the most extreme incomes, as superstar theory predicts.

Next, I test the effect of television on the rest of the distribution and continue to repeat the DID analysis for lower income ranges. Figure 1, panel B also plots the coefficients from these DID regressions. The empirical estimates closely mirror the theoretical predictions in panel A. The right-most point reports the results on extreme income growth just discussed. Moving to the next-lower income range between the ninetieth and ninetieth percentiles, I find that television still has some positive effects, but the effects are substantially smaller compared to the impact on at the very top. This confirms that the impact of SRTC diminish rapidly, even within the top tail of the distribution (confirming (ii) in Proposition 1). Adverse consequences become visible at slightly lower income levels, and all income ranges from the twenty-fifth to the ninetieth percentile are negatively affected. Television thus hollows out the middle of the income distribution ((iii) in Proposition 1). At the same time, the share of low-paid entertainers increases. These results thus confirm the predictions of (i)–(iii) in Proposition 1.

Note that "import" competition could also contribute to the adverse employment effects for lower-ranked talents, as viewers of local live entertainers may switch to watching TV shows from neighboring areas instead. However, such import competition would also result in declining local entertainer wages, and the fact that we see strong wage *growth* at the top suggests that the import effects in this setting, if they exist, are not strong enough to offset the superstar effects.

Alternative closely related outcome variables are incomes at different percentiles of the wage distribution. Results for wage percentiles are reported in the online Appendix, Section C3. The predictions for wage percentiles can be obtained by rearranging (1), and there is thus a one-to-one correspondence between wage results and the baseline results presented here. An advantage of the baseline results over quantile regressions is that the denominator of the outcome variable p_ω can be held fixed, as described above. This prevents spurious results from exits at the bottom end of the wage distribution, which would artificially raise top wage percentiles.

B. *Robustness Tests*

The key identification assumption of the DID approach is that TV launches are unrelated to spurious local shocks or trends that might similarly affect entertainer wages and employment. The television setting offers three compelling ways to probe this crucial assumption.

The first check relies on the *timing* of treatment effects. Specifically, we expect that effects that arise with the launch of a station should disappear after the demise of local filming. This is exactly what the blue line in Figure 3 shows. By 1970, after the invention of videotape, the differences between treated and untreated locations revert back to their pretreatment levels. Differences between treatment and control groups only last for the duration of local television filming. There are thus no differential trends that create permanent differences between treatment and control areas. The career dent for local stars is again well illustrated by Korla Pandit. His attempt to acquire national fame failed, and by the 1960s he reportedly returned to teaching piano lessons and playing various live venues, from mall openings to concert halls.

A second powerful test of spurious effects is generated by the interruption of the television rollout. Specifically, we can verify that places where station launches were unexpectedly blocked—that is, places with "frozen stations"—do not exhibit the same superstar effects that are observed in places that did launch. This is a placebo test for spurious local labor market shocks around the time of planned launches. Conventional pre-trend checks focus on trends before the treatment, but with the blocked station experiment we can additionally test for spurious shocks at the time of and after the planned TV launch date. The test is implemented in a dynamic DID analysis that compares the share of entertainers in the top 1 percent of US workers in untreated areas versus areas that narrowly missed out on launches due to the rollout interruption. The red line in Figure 3 shows that blocked locations have no spurious changes before, after, or during the time of blocked launches. These results are precisely estimated and rule out even relatively small violations of the parallel trends assumption.

Third, since television only changed the production function of a handful of occupations, we can use other occupations for an additional placebo test. If TV assignment is orthogonal to local labor market conditions, we would expect that such placebo occupations would be unaffected. Different from the previous test, this test analyzes spurious top-income shocks in the same local labor market as the TV launch. An ideal placebo group would be able to pick up changes in top income in the local economy, and I therefore use the main high-paying occupations as placebo groups (i.e., medics, engineers, managers, and service professionals). As shown by the yellow line in Figure 3, there is indeed no effect on placebo occupations. Taken together, these parallel trend tests suggests that we are identifying the causal effect of television stations.

The absence of spurious shocks is consistent with archival records of FCC decision-making. Launch priority was based on predetermined local characteristics (e.g., population size) and is thus unresponsive to local shocks. The empirical results confirm that these rollout rules were followed through in practice. For completeness, I also perform alternative robustness checks with conventional pre-trends and triple differences (see online Appendix Section C3), and both also find no spurious effects.

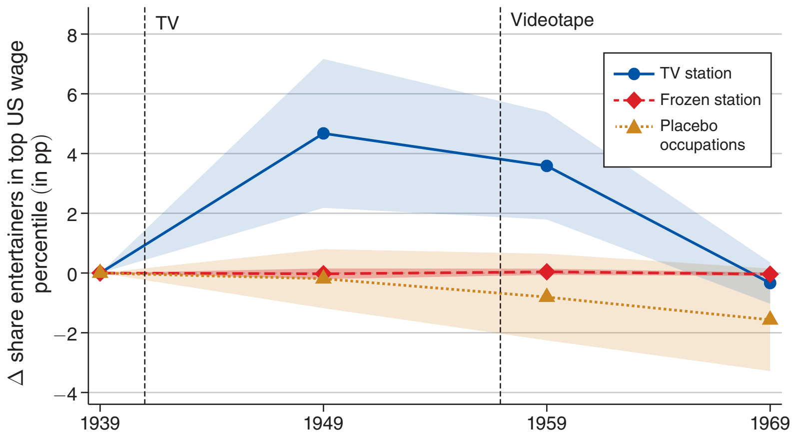

Figure 3. Dynamic Treatment Effect of TV on Changes in the Share of Entertainers in the Top US Wage Percentile

Notes: Figure plots treatment coefficients from three dynamic DID regressions. The specifications are dynamic versions of equation (2), with time-varying β_t. The outcome variable is the share of local entertainers (or placebo occupations) in the top percentile of the US wage distribution. Plot "TV station" shows the coefficient on TV_{mt}; plot "Frozen station" uses blocked TV stations instead of TV_{mt} as the treatment variable and uses untreated areas as the control group; plot "Placebo occupations" uses the same specification as the "TV station" line but for the placebo occupations described in the text. Vertical lines labeled "TV" and "Videotape" mark the beginning and end of local TV filming, respectively. The shaded areas mark the 95 percent confidence interval. Standard errors are clustered at the local labor market level.

C. *Employment Effects*

The final prediction is employment loss implied by (iv) in Proposition 1. These effects should occur in all areas that receive a television signal. Since a TV signal often extends beyond the local labor market where television filming takes place, more areas are affected by signal than by filming. To account for this, I modify the estimation equation (2) and code all areas with signal as treated. The signal data come from Fenton and Koenig (2020) and are a dummy with value one if signal is available in an area. The results show significant declines in employment (Table 1). The availability of signal reduces local entertainer employment by 13 percent, with similar results when controlling for demographics and local trends (columns 2 and 3).

Panel B performs a placebo test with blocked stations and shows again that signal of blocked stations had no effect. A final robustness test focuses on differential pre-trends in treatment and control areas during the decade before the treatment by including a lead of the treatment in the regression. To perform this test, I expand the sample period backward by a decade.[14] The point estimate on the lead variable coefficient is small and insignificant and thus shows parallel pre-trends in the lead-up to TV signal (panel C, column 4).

[14] This sample expansion is feasible since consistent employment data are available in the 1930 census.

Table 1—Effect of TV on Entertainer Employment

	ln(*Employment in Entertainment*)			
	(1)	(2)	(3)	(4)
Panel A. Sample 1940–1970				
TV signal$_t$	−0.128	−0.114	−0.139	
	(0.061)	(0.061)	(0.062)	
Panel B. Placebo sample 1940–1970				
Placebo TV signal$_t$	0.053	0.044	0.053	
	(0.083)	(0.083)	(0.084)	
Panel C. Sample 1930–1970				
TV signal$_{t+1}$				0.039
				(0.033)
TV signal$_t$	−0.133	−0.127	−0.133	−0.123
	(0.059)	(0.059)	(0.061)	(0.060)
Number of CZ cluster	722	722	722	722
Year-Occupation FE	Yes	Yes	Yes	Yes
CZ FE	Yes	Yes	Yes	Yes
Demographics	—	Yes	—	—
CZ level trends	—	—	Yes	—

Notes: The table shows the effect of television signal on local entertainer employment. Outcome variable ln(*Employment in Entertainment*) is the inverse hyperbolic sine of employment in entertainment. *TV signal* is a dummy that takes the value 1 if signal is available in a commuting zone (CZ) and *Placebo TV signal* if blocked stations would have brought TV signal. Column 2 controls for median age, percent female, percent minority, population density, and trends for urban areas. Column 3 controls for a separate linear trend for each CZ. Subscript $t+1$ refers to the lead of the treatment variable. Panels A and B include 13,718 CZ-year-occupation observations and panel C 17,328 observations. Standard errors are reported in parentheses and are clustered at the local labor market level.

Sources: TV signal from Fenton and Koenig (2020) and labor market data from US censuses 1930–1970

D. *Alternative Effect Channels*

For the interpretation of the results, it is useful to distinguish between two potential mechanisms: migration of entertainers and changing returns to talent. The census asks individuals if they migrated recently. I use this information to test for entertainer migration responses and find very small effects. The point estimates are negative, and confidence intervals are tight (Table 2, panel A). Migration thus appears to contribute little to the results. A potential explanation for the limited mobility response is that early shows tended to focus on local events, following the tradition of vaudeville, and thus did not translate easily to other locations. We can use the mobility estimates to bound the impact of migration. The central estimates suggest that mobility plays next to no role in the results; even at the upper bound of plausible values, the migration channel can only explain a quarter of the total effect.

A related concern is commuting across local labor market boundaries. Such behavior would downward bias the estimates by spreading the impact of local shocks beyond the boundary defined by commuting zones. Commuting is arguably easiest between neighboring areas, and we can thus alleviate the impact on the results by excluding areas that are adjacent to television launch locations from the analysis. Results that exclude such neighboring areas show very similar effects to the baseline, indicating that commuting plays a minor role in these findings (Table 2, panel B).

A further potential concern is that television changed the type of talent required of entertainers. As a result, television may have changed the distribution of talent

Table 2—TV and Migration between Labor Markets

	(1)	(2)	(3)
Panel A. Share entertainers who migrated			
Local TV stations	−0.014	−0.017	−0.010
	(0.015)	(0.015)	(0.020)
Sample	Full	Full	Full
Number of CZ cluster	722	722	722
Panel B. Entertainers among top 1 percent of US earners (excluding CZs adjacent to treated CZs)			
Local TV stations	4.31	4.49	6.17
	(1.31)	(1.30)	(2.27)
Sample	No adjacent CZ	No adjacent CZ	No adjacent CZ
Number of CZ cluster	568	568	568
Year-Occupation FE	Yes	Yes	Yes
CZ FE	Yes	Yes	Yes
Demographics	—	Yes	—
CZ level trends	—	—	Yes

Notes: The table tests the effect of local TV launches on entertainer migration. Outcomes: panel A, the fraction of entertainers who moved; panel B, share of entertainers among the top 1 percent of the US wage distribution, excluding CZs that share a border with treated CZs. All regressions control for CZ, occupation-specific time fixed effects and local filming cost in years after the invention of videotape. Entertainers are actors, athletes, dancers, entertainers not elsewhere classified, and musicians. Column 2 controls for median age and income, percent female, percent minority, population density, and trends for urban areas. Column 3 controls for a separate linear trend for each CZ. Sample: 13,718 observations and 722 CZs. Demographic data are missing for one CZ in 1940 and thus reduces the sample in column 2. The exclusion of CZs in panel B reduces the sample to 10,792 observations and 568 CZs. Observations are weighted by local labor market population. Standard errors are reported in parentheses and are clustered at the local labor market level.

Sources: US censuses 1940–1970

rather than returns to talent. The talent distribution is not directly observable, but historic description of television recruiting at the time suggests that the types of talent remained the same. Early television relied heavily on established show formats and often broadcast vaudeville shows (for an overview, see Murray (1999)). *Variety* magazine reported on the tensions that resulted from television poaching stars from established shows: "Criticism is being advanced in the trade that television so far has not kept its promise of developing its own talent." The television industry responded to this criticism and actively encouraged poaching, arguing that "stars are not going to be made by television. Television is going to be made by stars. So—let's go out and get them!"[15]

As a robustness test, we can probe the assumption of a stable talent distribution indirectly. This assumption implies that people maintain their rank in the distribution, while changes in the distribution would imply leapfrogging of individuals. To investigate leapfrogging, I digitize "who is who" lists of 1950 TV stars and merge individuals in these lists to their 1940 census records to build a small panel. The 1940 earnings data enable me to analyze earning ranks of later TV stars in the pre-TV period. The panel data show that in 1940, before television, roughy 60 percent of the later TV stars were already in the top wage decile and less than 5 percent were in

[15] See, respectively, Bob Stahl, "Where's That New TV Talent? Medium Scored for Its Laxity," *Variety*, October 26, 1949: 1, and "Video Needs Comedy: Tele-viewers Prefer Variety Show," *Television World*, May 24, 1948: 3.

the bottom decile. Eventual television stars were thus already disproportionally high paid before television, and television did not generate major leapfrogging (for data details, see online Appendix Section C3). Both historic sources and the data thus suggest that early television stations targeted the same talents who were successful in traditional entertainment.

IV. Conclusion

It has been 40 years since Sherwin Rosen (1981) presented his elegant superstar theory. In this influential work, Rosen shows how scale-related technological change can serve as a driving force in the generation of income inequality, particularly at the top end of the income distribution.

This paper provides the first direct test of this theory, using a simple natural experiment, and finds clear evidence that scale-related technological change can generate superstar effects, including income concentration at the top. The basis for the test is the increase in the market reach of entertainers that arose during the staggered introduction of television. The launch of a TV station increased audiences of star entertainers and created high-paid superstar entertainers. The income distribution skewed to the right, with escalating effects as we move up toward the top of the wage distribution. At the same time, the middle of the distribution is hollowed out as the share of entertainers with average incomes declines significantly and many lesser stars lost their jobs.

Technical change is, however, unlikely to generate superstar effects in all sectors of the economy. Superstar effects arise only in sectors where talent is heterogeneous and unique; we expect superstars to be less important (or not important at all) in settings where individual-level talent is highly substitutable. The production technology thus plays an important role, and not all scale-related technologies lead to superstar effects. An interesting avenue for future research is to explore which other sectors meet the conditions for superstar effects and to quantify how the magnitude of these effects vary across different sectors of the economy.

A broad literature has recognized that a better understanding of superstar effects is important not only from a scientific standpoint but also for policy decisions. Top earners are one of the main sources of tax revenue, and recent research shows that superstar effects could have substantial effects on the optimal design of taxes (Scheuer and Werning 2017). Moreover, superstar effects might influence the potential benefits from policies that reduce economic concentration and may explain economic divergence between regions (Eckert, Ganapati, and Walsh 2019). Scale-related technological change is shaping many sectors of the economy, and it is thus important that we improve our understanding of the far-reaching economic consequences.

REFERENCES

Acemoglu, Daron. 1998. "Why Do New Technologies Complement Skills? Directed Technical Change and Wage Inequality." *Quarterly Journal of Economics* 113 (4): 1055–89.

Acemoglu, Daron, and David H. Autor. 2011. "Skills, Tasks and Technologies: Implications for Employment and Earnings." In *Handbook of Labor Economics*, Vol. 4B, edited by O. Ashenfelter and D. Card, 1043–171. Amersterdam: Elsevier.

Akerman, Anders, Ingvil Gaarder, and Magne Mogstad. 2015. "The Skill Complementarity of Broadband Internet." *Quarterly Journal of Economics* 130 (4): 1781–824.
Autor, David H. 2014. "Skills, Education, and the Rise of Earnings Inequality Among the 'Other 99 Percent.'" *Science* 344 (6186): 843–51.
Autor, David H., and David Dorn. 2013. "The Growth of Low-Skill Service Jobs and the Polarization of the US Labor Market." *American Economic Review* 103 (5): 1553–97.
Autor, David H., Claudia Goldin, and Lawrence F. Katz. 2020. "Extending the Race between Education and Technology." *AEA Papers and Proceedings* 110: 347–51.
Autor, David H., Lawrence F. Katz, and Melissa S. Kearney. 2008. "Trends in U.S. Wage Inequality: Revising the Revisionists." *Review of Economics and Statistics* 90 (2): 300–323.
Autor, David H., Frank Levy, and Richard J. Murnane. 2003. "The Skill Content of Recent Technological Change: An Empirical Exploration." *Quarterly Journal of Economics* 118 (4): 1279–333.
Bartel, Ann, Casey Ichniowski, and Kathryn Shaw. 2007. "How Does Information Technology Really Affect Productivity? Plant-Level Comparisons of Product Innovation, Process Improvement, and Worker Skills." *Quarterly Journal of Economics* 122 (4): 1721–52.
Beaudry, Paul, Mark Doms, and Ethan Lewis. 2010. "Should the Personal Computer Be Considered a Technological Revolution? Evidence from U.S. Metropolitan Areas." *Journal of Political Economy* 118 (5): 988–1036.
Card, David, and John DiNardo. 2002. "Skill-Biased Technological Change and Rising Wage Inequality: Some Problems and Puzzles." *Journal of Labor Economics* 20 (4): 733–83.
Caselli, Francesco, and Alan Manning. 2019. "Robot Arithmetic: New Technology and Wages." *American Economic Review: Insights* 1 (1): 1–12.
Célérier, Claire, and Boris Vallée. 2019. "Returns to Talent and the Finance Wage Premium." *Review of Financial Studies* 32 (10): 4005–40.
Cook, Philip J., and Robert Frank. 1995. *The Winner-Take-All Society*. New York: The Free Press.
Eckert, Fabian, Sharat Ganapati, and Conor Walsh. 2019. "Skilled Tradable Services: The Transformation of U.S. High-Skill Labor Markets." Unpublished.
Feigenbaum, James, and Daniel P. Gross. 2020. "Automation and the Fate of Young Workers." NBER Working Paper 28061.
Fenton, George, and Felix Koenig. 2020. "Labor Supply and Innovation in Entertainment: Evidence from TV." Unpublished.
Gabaix, Xavier, and Augustin Landier. 2008. "Why Has CEO Pay Increased So Much?" *Quarterly Journal of Economics* 123 (1): 49–100.
Gabaix, Xavier, Augustin Landier, and Julien Sauvagnat. 2014. "CEO Pay and Firm Size: An Update After the Crisis." *Economic Journal* 124 (574): 40–59.
Garicano, Luis, and Thomas N. Hubbard. 2009. "Specialization, Firms, and Markets: The Division of Labor Within and Between Law Firms." *Journal of Law, Economics, and Organization* 25 (2): 339–71.
Gentzkow, Matthew. 2006. "Television and Voter Turnout." *Quarterly Journal of Economics* 121 (3): 931–71.
Gentzkow, Matthew, and Jesse Shapiro. 2008. "Preschool Television Viewing and Adolescent Test Scores: Historical Evidence from the Coleman Study." *Quarterly Journal of Economics* 123 (1): 279–323.
Kaplan, Steven N., and Joshua Rauh. 2010. "Wall Street and Main Street: What Contributes to the Rise in the Highest Incomes?" *Review of Financial Studies* 23 (3): 1004–50.
Kaplan, Steven N., and Joshua Rauh. 2013. "It's the Market: The Broad-Based Rise in the Return to Top Talent." *Journal of Economic Perspectives* 27 (3): 35–56.
Katz, Lawrence F., and Kevin M. Murphy. 1992. "Changes in Relative Wages, 1963–1987: Supply and Demand Factors." *Quarterly Journal of Economics* 107 (1): 35–78.
Koenig, Felix. 2023. "Replication data for: Technical Change and Superstar Effects: Evidence from the Rollout of Television." American Economic Association [publisher], Inter-university Consortium for Political and Social Research [distributor]. https://doi.org/10.3886/E162421V1.
Krueger, Alan B. 2005. "The Economics of Real Superstars: The Market for Rock Concerts in the Material World." *Journal of Labor Economics* 23 (1): 1–30.
Krueger, Alan B. 2019. *Rockonomics: What the Music Industry Can Teach Us About Economics and Life*. London: John Murray.
Lemieux, Thomas. 2006. "Increasing Residual Wage Inequality: Composition Effects, Noisy Data, or Rising Demand for Skill?" *American Economic Review* 96 (3): 461–98.
Michaels, Guy, and Georg Graetz. 2018. "Robots at Work." *Review of Economics and Statistics* 100 (5): 753–68.

Murray, Susan. 1999. "'Hitch Your Antenna to the Stars!' Early Television and the Renegotiation of Broadcast Stardom." PhD diss. University of Texas at Austin.

Rosen, Sherwin. 1981. "The Economics of Superstars." *American Economic Review* 71 (5): 845–58.

Sattinger, Michael. 1975. "Comparative Advantage and the Distributions of Earnings and Abilities." *Econometrica* 43 (3): 455–68.

Sattinger, Michael. 1979. "Differential Rents and the Distribution of Earnings." *Oxford Economic Papers* 31 (1): 60–71.

Scheuer, Florian, and Ivan Werning. 2017. "The Taxation of Superstars." *Quarterly Journal of Economics* 132 (1): 211–70.

Terviö, Marko. 2008. "The Difference That CEOs Make: An Assignment Model Approach." *American Economic Review* 98 (3): 642–68.

Tinbergen, Jan. 1956. "On the Theory of Income Distribution." *Weltwirtschaftliches Archiv* 77 (2): 155–75.

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