component, which calculates the extra growth that occurs because industries grow at di erent rates locally than they do nationally.

In my notation, this can be translated as follows:

$$X_{t,z} = X_{o} \overset{\text{\National Component"}}{(}$$

$$= \sum_{o} (X_{o,t}) \quad NE_{o,t,z}/NE_{t,z}$$

I posit that there is some redundancy in Bartik's terminology. Although Bartik refers to,

$$(X_{o,t} \{ X_{t}) \quad NE_{o,t,z}/NE_{t,z}$$

as the Share Component, the Share itself is surely just,

$$NE_{o,t,z}/NE_{t,z}$$

That which Bartik calls the Shift Component,

$$(X_{o,t,z} \{ X_{o,t}) \quad NE_{o,t,z}/NE_{t,z}$$

also contains the Share. I call rather $X_{o,t,z}$ the Shift, and $X_{o,t}$ the Delocalized Shift. In either case, the steps for converting the accounting identity into the instrumental variable are equivalent, only said in a di erent way. That is, removal of what Bartik calls the Shift Component is equivalent to delocalization of what I call the Shift. In either case, the accounting identity can be written as,

$$X_{t,z} = \sum_{o} X_{o,t,z} \quad NE_{o,t,z}/NE_{t,z}$$

and the instrument is,

$$\tilde{X}_{t,z} = \sum_{o} X_{o,t} \quad NE_{o,t,z}/NE_{t,z}$$

The main step in converting $X_{t,z}$ to $\tilde{X}_{t,z}$ is the Shift Delocalization, $X_{o,t,z}$! $X_{o,t}$, and the secondary step is the Share Lag, $NE_{o,t,z}/NE_{t,z}$! $NE_{o,t,z}/NE_{t,z}$.

Bound and Holzer (2000), also closely related to Bartik (1991) and Blanchard and Katz (1992), study in particular how the impacts of local job growth fall di erently across racial

and demographic groups. Their Shift-Share instrument is also the same,

Critically, this lagged Share vector (of industrial shares) is assumed to be causally prior to (exogenous with respect to) future job growth. The main argument for this exogeneity is that industrial shares are deep characteristics of localities (MSAs) z, arising from forces outside the model, such as geography, technology, and historical accident. The lag provides an auxiliary argument, applicable but not conclusive (on its own) in any context: Anything in the past is likely to be causally to prior to anything in the present or future.

I argue that, although less common in Shift-Share instruments than Frozen Lags are, Updating Lags are usually better. In contrast to Frozen Lags, which lag all t to a common base period t_0, lagging $(z, t) \rightarrow (z, t_0)$, Updating Lags rather maintain a common distance in time between each t and its lag $(z, t) \rightarrow (z, t-1)$. As discussed in the previous paragraph, the purpose of either kind of lag is to help insure that the Shares are causally prior to the dependent variable in the present (t), although this is not the main argument for the Shares' exogeneity. Either kind of lag accomplishes this purpose equally, as either is prior in time to the present (t). However, Frozen Lags have the downside that because the base period t_0 is a di erent distance in time from each t in the panel, it is likely to be far more relevant for the earlier time periods - those closer to t_0 - than it is for the later time periods. The magnitude of this problem is likely to depend on the span of time under study.

In addition to Frozen or Updating Lags, Shares may be averaged over all lags and leads, or not lagged at all. Averaging over all lags and leads may be sensible particularly if the number of time periods is large, as in Nunn and Qian (2014). With a large number of time periods, that is, the role of any one time period's values in determining the averages for z is small. Hence these averages can be assumed to re ect intrinsic characteristics of z, causal rst movers rather than endogenous reactions. However, perhaps most thematically important to consider is eac(eac)27no9lly

in any lag.

4.2 Di erencing and Fixed E ects

Although Shift-Share instruments provide a powerful framework for bypassing reverse causality, it should be noted that they do not o er anything novel with respect to omitted variable bias. Rather, Shift-Share instruments rely on standard methods for unobservables: di erencing, xed e ects, and other controls. Di erencing and xed e ects are methods meant to account for the sum total of all unobserved e ects. However, neither of these is perfect, and the potential for unobserved information to play a confounding role is ultimately unavoidable in any setting.

The stereotypical Shift-Share instrument is accompanied by a di erencing method. This can be understood as follows. Suppose the model is of a form,

$$Y_{t,z} = b \; X_{t,z} + d_t + d_z + d_{t,z} \tag{2}$$

where $X_{t,z}$ is the endogenous regressor of interest, and d are unobserved factors. As we know, the endogenous regressor $X_{t,z}$ can be written as a product of Shift and Share components (accounting identity),

$$X_{t,z} = \underbrace{X_{o,t,z}}_{\text{Shift}} \; \underbrace{\frac{N_{o,t,z}}{N_{t,z}}}_{\text{Share}} \tag{3}$$

The Shift-Share in6 Tf 8.775 -2.0 5 89552 Thar(di ([(Nsi 78(t)]1F26)-1(6.28 Td [(.)]TJ/F15 11.9552 Tf

$X_{o,t,z}$

d.

Stereotypically, a time di erence of (2) is taken to eliminate the time-invariant unobserved component, d_z. The di erenced equation is,

$$(Y_{t,z} \{ Y_{t,z}) = b \ (X_{t,z} \{ X_{t,z}) + (d_t \{ d_t) + (d_{t,z} \{ d_{t,z}) \tag{5}$$

with

$$\tilde{X}_{t,z} \{ \tilde{X}_{t,z} = \sum_o \underbrace{z}_{\text{Shift}} \{ \underbrace{z}_{\text{Share}} \{$$
$$(X_{o,t} \{ X_{o,t}) \quad N_{o,t,z} \quad N_{t,z}$$

straightforwardly serving as the instrument for $(X_{t,z} \{ X_{t,z})$.[10] Estimation of (5) can recover b without fear of confounding from d_z, because the time di erence has eliminated d_z. Or, rather than taking the time di erence, an alternative method to accomplish the same purpose is to impose xed e ects $\hat{d}_z$ to absorb d_z in the estimation of (2). In either case, time period xed e ects $\hat{d}_t$ are imposed as well to absorb d_t.

A weakness of either di erencing or xed e ects $\hat{d}_z$ is that, although both nullify time-invariant unobservables d_z completely, neither does anything whatsoever to nullify time-varying unobservables $d_{t,z}$. There is typically no reason to assume that all potentially confounding unobservables would be time-invariant, and hence time-varying unobservables are the most important blind spot of many Shift-Share instruments. Alternatively, time-varying regional e ects $\hat{d}_{t,Z}$ may be imposed to absorb some time-varying unobservables, as well as some time-invariant unobservables. (Regions Z are closely related clusters of Localities z.)[11] The optimal balance of such e ects should absorb the most important potentially confounding unobserved factors of both types, that is, time-varying and time-invariant.

5 Novel Variants

Autor, Dorn and Hanson (2013) study the e ects of import competition on labor market

[10] Often $(X_{t,z} \{ X_{t,z})$ is written rather as the original $X_{t,z}$, and $(X_{o,t} \{ X_{o,t})$ as the original $X_{o,t}$.

[11] Time-varying e ects at the z level $\hat{d}_{t,z}$ would absorb the entire panel, leaving nothing to be explained by any regressor(s) of interest.

outcomes for US workers, that is, unemployment, labor force participation, and wages. The endogenous explanatory variable of interest is a change in labor market exposure to Chinese imports. Total China-to-US import volume is I_t. The basic idea is that these imports I_t are in competition with the output of US workers: The competitive impact of I_t on US workers is spread out equally, so that the impact per individual US worker is I_t/NE_t, where NE_t is the total number of workers in the US. The change in exposure can be written as

$$X_{t,z} = (I_t \{ I_{t\{1})/NE_{t\{1} \qquad (6)$$

for any US Commuting Zone z in which there are any workers. This $X_{t,z}$ is constant over z, assuming there are any workers in z, because the impact is assumed to be spread equally over workers nation-wide.

Instead of (6), which is an oversimplication, the authors suppose rather that the competitive impact of Chinese imports in industry o is spread equally nation-wide over all US workers in industry o.

$$X_{o,t,z} = (I_{o,t} \{ I_{o,t\{1})/NE_{o,t\{1} \qquad (7)$$

Alhough specic by industry o, $X_{o,t,z}$ is still constant over z, for the same reason that equation (6)'s $X_{t,z}$ would be constant over z. However, the unconditional average impact per worker in z now depends on the industrial makeup of z, because each industry-specic impact $X_{o,t,z}$ ¾ X_{t1} = (I

the Shift $X_{o,t,z}$ is unlike that in the classical setting, because it is already constant over z. Typically, a Shift Delocalization involves replacing local Industry averages $X_{o,t,z}$ with national Industry averages $X_{o,t}$. However, as discussed in the previous paragraph, it is already the case that $X_{o,t,z} = X_{o,t}$, due to the way in which the exposure variable itself is de ned. But Autor, Dorn and Hanson (2013) go further than this, delocalizing their Shift on a higher level. They replace nation-wide industry averages $X_{o,t}$ with world-wide averages $X^0_{o,t}$.

$$X^*_{t,z} = \underbrace{X_{o,t}}_{\text{Shift}} \; \underbrace{\frac{X^0_{o,t}}{NE_{o,t-1,z}}}_{\text{Share}} \; \underbrace{NE_{t-1,z}}_{} \tag{9}$$

$$X^0_{o,t} = (I^0_{o,t} - I^0_{o,t-1})/NE_{o,t-1}$$

I^0_o is export volume from China industry o world-wide, to other high income countries besides the US.

Nunn and Qian (2014) study the e ect of food aid on armed con ict in countries receiving the aid. Although food aid might be expected to cool tensions between opposing factions, often rather the opposite is observed, as armed theft of the aid ignites further con ict. There is also a strong channel for reverse causality, however: Countries experiencing con ict may be more likely to receive aid.

The endogenous variable of interest $X_{t,z}$ for Nunn and Qian is the the amount of food aid (wheat) that country z receives from the US in year t. An accounting identity for this variable is,

$$X_{t,z} = \underbrace{I_{t,z}}_{\text{Share}} \; \underbrace{X_{t-1}}_{\text{Push}} \tag{10}$$

where $I_{t,z}$ is a binary variable equal to one if country z is selected to receive wheat aid in year t, and X_{t-1} is the quantity of wheat produced in the US in the previous year (scaled by the number of countries to receive the aid). This quantity is lagged because it takes a one-year cycle for the wheat to transition from production to distribution. Their instrument

is the in ow of immigrant workers of group j, $NI_{j,t,z}$, to each Metropolitan Statistical Area (MSA) z in the US. This in ow can be expressed as the sum of in ows from each of various countries of origin, o.

$$X_{j,t,z} = NI_{j,t,z} = \sum_{o} NI_{j,o,t,z}$$

This can be multiplied by $NI_{o,t,z}/NI_{o,t,z}$ and $NI_{o,t}/NI_{o,t}$ to yield the following accounting identity:

$$X_{t,z} = \sum_{o} \underbrace{NI_{j,o,t,z}/NI_{o,t,z}}_{\text{Shift}} \underbrace{NI_{o,t,z}}_{\text{Share}} \underbrace{NI_{o,t}}_{\text{Push}} \tag{12}$$

$NI_{o,t}$ is the total in ow to the US of immigrant workers from country of origin o. $NI_{o,t,z}/NI_{o,t}$ are the fraction of immigrant workers from country of origin o who accrue to each MSA z. Abstractly, $NI_{o,t,z}/NI_{o,t}$ are Localities' Shares of Industries (see Section 2), with countries of origin o as abstract Industries. $NI_{j,o,t,z}/NI_{o,t,z}$ are the fraction of immigrant workers from country of origin o to MSA z who are workers in occupation group j.

To arrive at an instrument, Card delocalizes the Shifts $NI_{j,o,t,z}/NI_{o,t,z}$ over z, and lags the Shares $NI_{o,t,z}/NI_{o,t}$ to a historical base period t.[12]

$$\tilde{X}_{t,z} = \sum_{o} \underbrace{NI_{j,o,t}/NI_{o,t}}_{t_{gj}} \underbrace{NI_{o,t,z}}_{l_{gc}} \underbrace{NI_{o,t}}_{M_g}$$

Similarly as in a classical Shift-Share instrument, the Shares represent that which is most exogenous about $X_{t,z}$ per Locality z. Newly arriving immigrants tend to move to enclaves established by earlier immigrants from the same source country, not for endogenous labor demand reasons, but rather due to cultural and family ties. The lag provides an additional guarantee of this exogeneity.

Also like in a classical Shift-Share instrument, the local Shifts would be highly endogenous, and therefore are delocalized over the cross section. These local Shifts $NI_{j,o,t,z}/NI_{o,t,z}$ give the occupational makeup of immigrant workers entering each city. Occupational makeup

[12] t_{gj}, l_{gc}, M_g are the notation actually used by Card (2001) for these objects.

is driven heavily by the local economy's labor demand, which is endogenous in this setting. The Delocalized Shifts $NI_{j,o,t}/NI_{o,t}$ replace the occupational makeup entering each city with

$P_{h,t,z} = N_{h,t,z}/N_{t,z}$, which I call Bin Shares, are the fractions of the local z population who fall into each bin h. The cuto s of the bins h are shared in common over the nation, so the Bin Shares vary by Locality z. For example, more unequal Localities z will tend to have higher $P_{h,t,z}$ values for the highest and lowest bins h. To arrive at an instrument, the authors lag the Bin Shares to a historical base period.

$$\tilde{x}_{t,z} = \frac{\sum_h \underbrace{P_{h,t,z}}_{\text{Share}} \underbrace{Y_{h,t}}_{\text{Push}}}{\sum_h \underbrace{P_{h,t,z}}_{\text{Share}} \underbrace{Y_{h,t}}_{\text{Push}}} \qquad (15)$$

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In Section 2, I presented a general formula for classical Shift-Share instruments, applicable to any endogenous explanatory variable $X_{t,z}$ which is a mean over individuals who can be rearranged into subgroups to form Shares. In this section, I derive analogous formulas for other distribution summaries, that is, besides the mean. As with the formula for the mean, basing the instrument on an accounting identity is a guide to relevance. That is, it provides the most natural approximation of the endogenous explanatory variable as a function of the exogenous factors.[14]

6.1 Variance and Skew

In Section 2, I considered any endogenous explanatory variable $X_{t,z}$ that is a mean over individuals i. Following from the de nitions of means and from the fact that,

$$\sum_{i \in t,z} X_i = \sum_{o} \sum_{i \in o,t,z} X_i \tag{16}$$

I showed that $X_{t,z}$ can be expressed as the Classical Accounting Identity,

$$X_{t,z} = \sum_{o} \underbrace{X_{o,t,z}}_{\text{Shift}} \cdot \underbrace{N_{o,t,z}/N_{t,z}}_{\text{Share}}$$

I now consider any endogenous explanatory variable $V_{t,z}$ that is a variance over individuals i.

$$V_{t,z} = N_{t,z}^{-1} \sum_{i \in t,z} (X_i - X_{t,z})^2 \tag{17}$$

[14] A rst stage consisting of all the lagged Shares as separate instruments, for example, may yield a higher overall t - but this would most likely be a case of over tting.

For readability, I suppress t subscripts throughout the remainder of Section 6.

$$V_z = N_z^{-1} \sum_{i \in z} (X_i - X_z)^2 \quad , \quad \sum_{i \in z} (X_i - X_z)^2 = N_z \; V_z \tag{18}$$

In addition to (16), it is helpful to apply the identity,

$$(X_i - X_z)^2 = (X_i - X_{o,z})^2 + ((X_i - X_z)^2 - (X_i - X_{o,z})^2) \tag{19}$$

(19) bene cially decomposes the moment into within-category and across-category components.

$$\begin{aligned} V_z &= N_z^{-1} \sum_{o \in z} \sum_{i \in o,z} (X_i - X_z)^2 \\ &= N_z^{-1} \sum_{o \in z} \Big(\underbrace{\sum_{i \in o,z} (X_i - X_{o,z})^2}_{\text{within-}o} + \underbrace{\sum_{i \in o,z} ((X_i - X_z)^2 - (X_i - X_{o,z})^2)}_{\text{across-}o} \Big) \end{aligned} \tag{20}$$

The within-category component is straightforward, as by de nition,

$$V_{o,z} = N_{o,z}^{-1} \sum_{i \in o,z} (X_i - X_z)^2 \quad , \quad \sum_{i \in o,z} (X_i - X_{o,z})^2 = N_{o,z} \; V_{o,z} \tag{21}$$

hopes of securing more desirable matches. Kearney and Levine (2014) discuss several other theories pertaining to single parenting directly, emphasizing rather hopelessness: Under-privileged women in more unequal markets may have little hope of securing decent marriage matches (or decent careers for themselves), anyway. Therefore, the burden of single parenting makes relatively little di erence to their life prospects.

In examining the relationship between inequality and single parenting propensity (or marriage rates), there is often an elephant in the room. Although both Gould and Paserman (2003) and Kearney and Levine (2014) use rich sets of control variables to test for alternative explanatory factors, neither clearly addresses the question of direct reverse-causal e ects of single parenting (or marriage rates) on inequality. Indeed, Chetty et al. (2014) nd single parenting to be the strongest and most robust single predictor of socioeconomic immobility:

motivate single parenting - including both the hope of Gould and Paserman (2003), and the hopelessness of Kearney and Levine (2014).

Although equation (41) represents all e ects of inequality on single parenting propensity, it does not represent any reverse e ects - that is, of single parenting on inequality.[16] For this reason, an ordinary regression estimation of (41) would be confounded by simultaneity bias, and fail to recover $b^{Inequality}$. The purpose of instrumenting is to restrict the information

local taxation and of crime rates, the instrument is valid for the same reason: present period single parenting rates cannot drive past values of the Shares. This raises the question: What advantage do Shift-Share instruments have over simply using lags as instruments? That is,

of interest. In the setting of Boustan et al. (2013), this question would be whether the local income distribution responds to future changes in local taxation and expenditure policy. Lower earning people for example, if accurately predicting future policy, may select into localities in which future taxation and expenditure are on an upward trajectory. With single parenting rates as the outcome of interest, an analogous confounding scenario may be that wealthier people avoid localities in which single parent homes are on the rise.

Where a lag instrument relies on the explanatory variable to not respond to future changes in the outcome variable, a Shift-Share instrument rather relies on only the Shares to not do so. To accomplish this purpose, it is vital that Shares represent deep characteristics of cross sectional units (Localities), such as can be viewed as causal rst movers of the economic system under study. The industrial pro le each Locality (the classical Share vector) meets this purpose because it arises from geographical and historical forces that are beyond the scope of the model. For example, shipping relies on access to water, and locations are bound to particular industries, such as Detroit to manufacturing, for historical reasons that cannot be easily adjusted.

Unlike classical industrial Shares, the Shares of the Lagged Bin Share instrument needn't coincide with anything particularly fundamental to localities. These Shares are Bin Shares, which simply map the local income distribution. They are sensitive to anything that alters the local income distribution, including selective migration of higher or lower earning individuals. As such, these Shares are more vulnerable to confoundedness by future expectations than Shares of a typical Shift-Share instrument would be. This is the ip side of lacking a Shift component that is delocalized over the cross section. The local averages that are most vulnerable to endogeneity would be in the Shift rather than the Share, and hence neutralized by the Shift delocalization.

Where the Lagged Bin Share Gini replaces the endogenous Bin Share with a lagged Bin Share, my Shift-Share Gini rather replaces it with a classical Shift-Share instrument for the Bin Share itself. Although it is its own kind of share, the Bin Share does not constitute the Share of a Shift-Share instrument, for two reasons that are ip sides of the same coin. First,

there is no corresponding Shift - that is, a component distinctive to each Locality that is delocalized in the instrument. Second, indeed because there is no Shift component to carry the regressor's local information that is most vulnerable to endogeneity, the Bin Share (even

8 Conclusion

This paper may be unique in focusing on the generative process by which a researcher may arrive at Shift-Share instruments. By deriving the instrument directly from an accounting identity of the explanatory variable, one can appreciate both the essential features of Shift-Share instruments, and the scope of their potential varieties. Using my simple approach for understanding Shift-Share instruments as modi ed accounting identities, I closely compare a wide variety of instruments from the literature. I then also develop general formulas for several new varieties - instruments for variances, skews, mean absolute deviations, and Gini coe cients.

As an empirical application, I measure the e ect of earnings inequality on rates of single parenting, using multiple alternative instruments for the Gini coe cient of earnings. The empirical results illustrate core themes from earlier in the paper. That is, Shift-Share instruments both delocalize (replace with nonlocal averages) the more endogenous part of the accounting identity (the Shift vector), and lag the more exogenous part of the accounting identity (the Share vector). Empirically, I show that instruments that do only one or the other - delocalize the Shift, or lag the Share - also correct bias, but only part way. Thus, although each of these steps - delocalizing the Shift, and lagging the Share - provides its own argument of exogeneity, both make meaningful contributions to the exogeneity of the Shift-Share instrument as a whole.

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