Web Appendix for:

Air Service and Urban Growth: Evidence from a Quasi-Natural Policy Experiment*

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A Theory Appendix

This section presents a simple framework that formalizes the process of urban growth. We follow the set-up in Glaeser, Scheinkman and Shleifer (1995), which we amend by allowing air services to enter both as a productivity shifter and as a local amenity. The main aim here is to provide guidance for the empirical analysis. We use the derived structural equation to obtain an estimation equation and then, in the main paper, discuss its virtues in terms of econometric identification.

Each metropolitan statistical area (MSA) is viewed as a separate open economy that shares a common (national) stock of capital and labor endowments. Free factor mobility ensures that capital and labor will be distributed across MSAs in equilibrium such that the rental rate and per-capita income, adjusted for local amenities, are equalized. A direct implication of this equilibrium outcome is that neither exogenous changes in labor supply, nor in saving rates, can be used as explanations for differences in urban growth. Instead, factors rooted in local fundamentals should be considered. In that respect, a common view in the regional development literature is to assume that MSAs differ only in the *level of productivity* and the *quality of life* determined by local amenities.

Let the total output in a metropolitan area be given by:

$$Y_{it} = Z_{it} f(L_{it}) \tag{1}$$

where Z_{it} represents the level of productivity in the metropolitan area i at time t, and L_{it} measures the population of the MSA i at time t.[1] $f(.)$ is assumed to be a Cobb-Douglas production function

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[1] The production function can be extended to include other factors of production as long as they are local and immobile, such as non-tradeable capital or government spending on local infrastructure, urban transportation,

that is common across urban communities:

$$f(L_{it}) = L_{it}^{\alpha} \tag{2}$$

Individuals derive utility U_{it} from the labor income they earn, denoted W_{it}, and the quality of life they enjoy in their community, labeled Λ_{it}.[2] The two components are assumed to enter the utility function multiplicatively:

$$U_{it} = W_{it}\Lambda_{it} \tag{3}$$

Workers get paid the value of their marginal product (with the output price normalized to one), which implies that labor income is given by:

$$W_{it} = \alpha Z_{it} L_{it}^{\alpha-1} \tag{4}$$

The quality of life term, Λ_{it}, captures a host of location specific factors. It is assumed to decrease in the population size of the metropolitan area, mainly because of the impact of size on housing prices, traffic congestion, crime, etc. It also varies with several other factors that are exogenous to the production technology such as, for example, local amenities. We summarize these factors, for now, by the vector Q_{it}. That is:

$$\Lambda_{it} = L_{it}^{-\delta} Q_{it} \tag{5}$$

where $\delta > 0$.

Free mobility of individuals ensures that utility is constant across space at a given point in time in equilibrium, i.e., $U_{it} = U_t, \forall i$. This also implies that changes in utility over time happen at the same rate across MSAs. Using equations (3)-(5), the following must hold for each metropolitan area:

$$\begin{aligned} \log\left(\frac{U_{t+1}}{U_t}\right) &= \log\left(\frac{W_{it+1}}{W_{it}}\right) + \log\left(\frac{\Lambda_{it+1}}{\Lambda_{it}}\right) \\ &= \log\left(\frac{Z_{it+1}}{Z_{it}}\right) + (\alpha - \delta - 1)\log\left(\frac{L_{it+1}}{L_{it}}\right) + \log\left(\frac{Q_{it+1}}{Q_{it}}\right) \end{aligned} \tag{6}$$

where the left hand side of equation (6) is identical across all MSAs. For this identity to hold for all i, it must be the case that population growth in every metropolitan area adjusts each period such that, given the productivity growth and any changes in local amenities, utility grows at a rate that is common across all communities. Therefore, from equation (6) we can express the rate of population growth as:

$$\log\left(\frac{L_{it+1}}{L_{it}}\right) = \frac{1}{1-\alpha+\delta}\left[\log\left(\frac{Z_{it+1}}{Z_{it}}\right) + \log\left(\frac{Q_{it+1}}{Q_{it}}\right)\right] + \kappa_t \tag{7}$$

with κ_t a constant.[3]

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etc. This extension is straightforward, but is not necessary for our empirical work, so we exclude them from our framework. Given that our identification strategy accounts for location specific time trends, under a constant rate of capital accumulation over time, the impact of non-tradeable capital and local infrastructure is implicitly controlled for.

[2] It is possible to extend the utility function to include consumption of intra-city transport (i.e., commuting) and consumption of land. Doing so would introduce congestion effects and rising rental rates for communities that witness a rapid growth in population and per-capita income. These disutility effects associated with economic growth provide additional counter-balance against regional expansionary forces.

[3] Formally, $\kappa_t \equiv \log\left(U_{t+1}/U_t\right)/(\alpha - \delta - 1)$.

Re-writing the labor income in equation (4) as an annual growth rate and substituting for population growth using equation (7), we can derive the following expression for the income growth at the MSA level:

$$\log\left(\frac{W_{it+1}}{W_{it}}\right) = \frac{1}{1-\alpha+\delta}\Big[\delta\log\left(\frac{Z_{it+1}}{Z_{it}}\right) + (\alpha-1)\log\left(\frac{Q_{it+1}}{Q_{it}}\right)\Big] + \omega_t \tag{8}$$

with $\omega_t \equiv (\alpha-1)\kappa_t$ a constant.

Most empirical studies on regional development and urban growth focus on identifying the determinants of population and income growth. For equations (7) and (8) to serve such a purpose, one needs to specify the stochastic process of productivity as well as the exogenous factors that define the appealing characteristics of an urban area. It is customary to include the initial (base year) conditions as the main determinants of the subsequent growth in productivity and quality of life, respectively. Of particular interest to this paper is the provision of air transport services, which we expect to have a direct effect on both the local productivity growth, as well as on the valuation consumers attach to that location.[4] Thus, we assume that:

$$\log\left(\frac{Z_{it+1}}{Z_{it}}\right) = (X_{it})'\gamma_1 + \beta_1\log\left(\frac{A_{it+1}}{A_{it}}\right) + \nu_{it} \tag{9}$$

$$\log\left(\frac{Q_{it+1}}{Q_{it}}\right) = (X_{it})'\gamma_2 + \beta_2\log\left(\frac{A_{it+1}}{A_{it}}\right) + \upsilon_{it} \tag{10}$$

where X_{it} is a vector of characteristics for MSA i observed in the base year t[5], and A_{it} denotes the volume of airline traffic in the metropolitan area i at time t (a proxy for the local aviation network).

Substituting equations (9) and (10) into (7) and (8) respectively, then replacing the structural coefficients with reduced form ones, and relabeling the log growth rates of the main variables for notational simplicity, we get:

$$\dot{L}_{iT} = \beta\dot{A}_{iT} + X_{iT_0}{}'\gamma + \varepsilon_{it} \tag{11}$$

$$\dot{W}_{iT} = \tilde{\beta}\dot{A}_{iT} + X_{it}{}'\tilde{\gamma} + \xi_{it} \tag{12}$$

where $\dot{K}_{iT} \equiv \frac{K_{iT_1}-K_{iT_0}}{T_1-T_0}$ for K $\in \{L, W, A\}$, with T indexing the interval $[T_0, T_1]$; and $\beta, \gamma, \tilde{\beta}, \tilde{\gamma}$ are parameters derived from the structure of the model.[6]

The coefficients of interest are β and $\tilde{\beta}$, respectively. We expect the effect of air traffic growth to be positive in a regression explaining the rate of growth of population, per-capita income, and employment respectively, across metropolitan areas.

[4] While counting air services as part of a location's amenities seems obvious, their impact on regional productivity may be less transparent. The discussion in footnote 5 suggests several channels that could explain the productivity effect of air service. They include technology diffusion, trade and agglomeration effects.

[5] The fact that the same vector X_{it} determines both the productivity and life quality growth rates is not restrictive as long as coefficients in both β and γ vectors are allowed to take zero values.

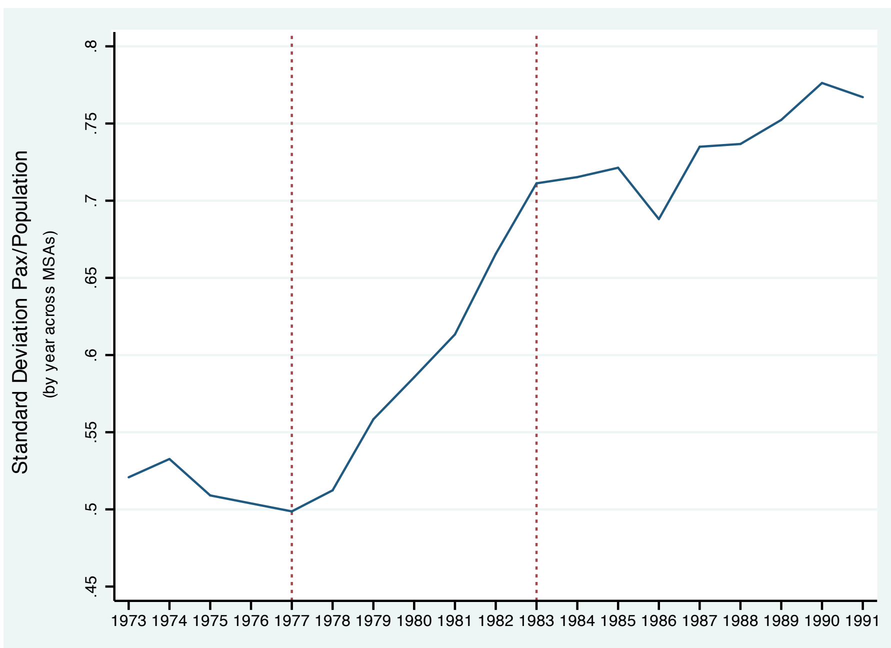
[6] Formally, $\gamma = (\gamma_1+\gamma_2)/(1-\alpha+\sigma)$; $\beta = (\beta_1+\beta_2)/(1-\alpha+\sigma)$; $\tilde{\gamma} = (\delta\gamma_1 + (\sigma-1)\gamma_2)/(1-\alpha+\sigma)$; and $\tilde{\beta} = (\delta\beta_1 + (\sigma-1)\beta_2)/(1-\alpha+\sigma)$.

B Data Appendix

B.1 Choice of Post-deregulation time window

We shorten the time horizons over which air traffic changes are observed in the post-deregulation period to limit the impact of reverse causality. We restrict our attention to the time window 1977-1983.

We choose year 1983 to mark the ending of the policy shock period because this is the year when the regulatory body, i.e., the Civil Aeronautic Board (CAB), was dissolved. In addition, Figure B1 provides further support to the suitability of year 1983. The plot tracks the standard deviation of air passengers per capita across the sample MSAs within each year, i.e., $st.dev.\left(ln\frac{A_{it}}{L_{it}}\right)$. Interestingly, during the regulatory period, the air traffic at city level was tightly linked to the population size. This dependency, however, is weakened by the shift to free market conditions. The increase in standard deviation since 1978 – justified by the transformations in the aviation industry following deregulation – seems to plateau after 1983, a possible sign that regulation was fully dismantled by then.



Source: Authors' Calculations

Figure B1: The Volatility of the Number of Passengers Per-Capita across Cities over Time

Note: This trend tracks by year the magnitude of the standard deviation of the ratio of air passengers per capita across the sample MSAs in a given year. The period 1977-1983 marks the transition period to a fully deregulated aviation industry.

B.2 Alternative Instrumental Variables Strategy: Policy Distortion Inferences based on the Residual Variation in Air Traffic

A second set of excluded instruments relies on data inferences to quantify the exogenous distortions to air services unwound by deregulation. In particular, we consider the counterfactual level of air traffic in city i at the end of the regulatory period, i.e., year 1977, had there not been any government regulation in place. We denote this by $A^*_{i,1977}$. We then define the policy distortion, Δ_i^{Policy}, as the difference between the counterfactual and observed levels of air traffic in that pre-deregulation year.[7] Using the formalized equations for the regulated and unregulated level of air traffic (i.e., equation (2) in the main paper), we can express Δ_i^{Policy} as:

$$\Delta_i^{Policy} \equiv lnA^*{}_{i,1977} - lnA_{i,1977} = -\widetilde{\alpha}_i - \widetilde{\delta} lnZ_{i,1977} \tag{13}$$

In the absence of regulatory distortions, i.e., $\alpha_i = 0$ and $\delta = 0$, any variation in Δ_i^{Policy} would only consist of white noise.

In the data, we infer the counterfactual air traffic level $A^*_{i,1977}$ based on out-of-sample predictions from a regression model of city level air traffic estimated on data from a period of unconstrained market decisions. We defer the details of this estimation procedure to the Data Appendix subsection B3.

We expect the inferred policy shock Δ_i^{Policy} to be positively correlated with the observed changes in air traffic post-deregulation. That is, communities that suffered from an undersupply of air services during the CAB regulatory days (i.e., $A_{i,1977} < A^*_{i,1977}$) should be more likely to witness a rapid growth in air traffic post deregulation (i.e., $\dot{A}_{i1} > 0$). Figure B2 gives support to this insight, revealing a tight positive correlation between the inferred regulatory distortion, Δ_i^{Policy}, and the observed air traffic changes in the aftermath of deregulation, i.e., 1977-1983. The correlation holds true even among the cities within the same size category.

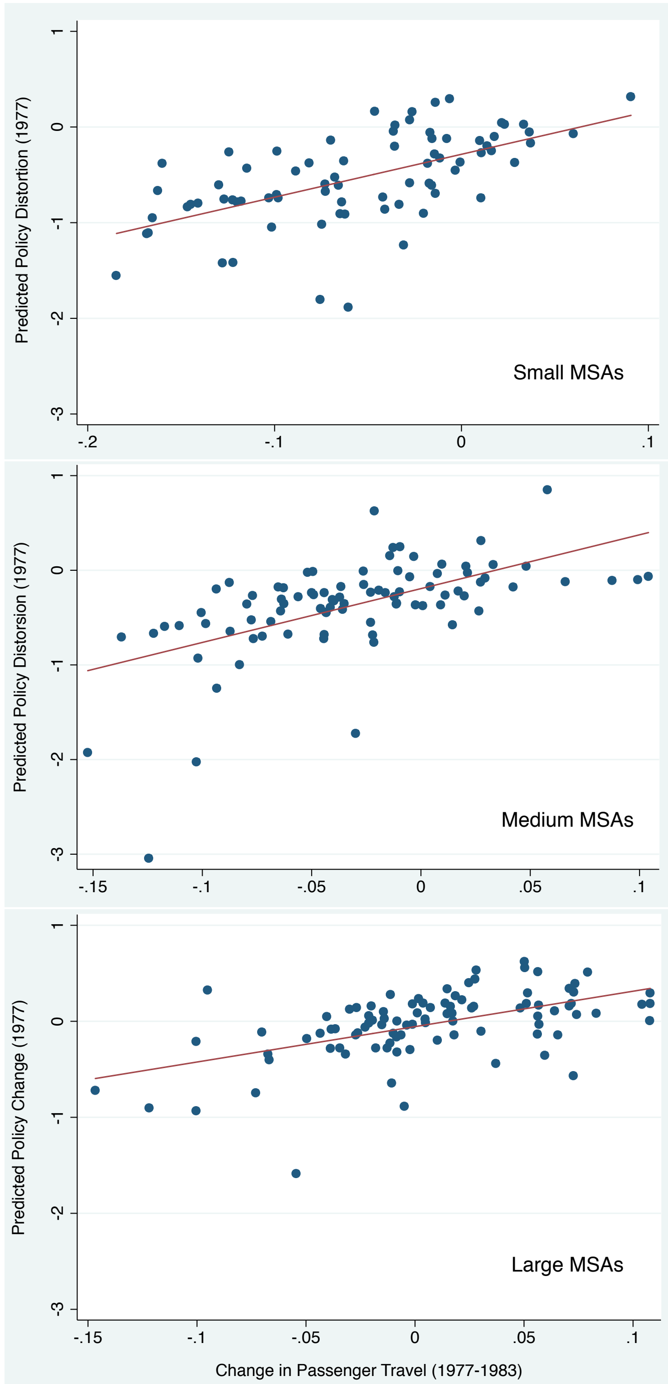
For Δ_i^{Policy} to be a valid instrument, it also needs to be uncorrelated with the residual from urban growth regressions. We can think of two reasons why that is the case. First, Δ_i^{Policy} is a difference of two terms. Since observable city characteristics such as size, industrial composition and prior rate of growth, are used to predict the counterfactual level of air traffic in addition to city fixed effects, then, by taking the difference in equation (13), Δ_i^{Policy} should be purged of any urban growth determinants. Second, the instrument is constructed using 1977 data, yet it is actually used in a regression explaining long-run urban growth over a period more distant in the future. In the results section we will provide more details on the significant time lag between the instrument and the city level outcome to be explained.

To strengthen the exogeneity of the proposed instrument, we interact Δ_i^{Policy} with each of the three MSA size categories. That is, we instrument for the air traffic changes of a city using the average policy distortion across all cities within the same MSA size category. Although, by construction, Δ_i^{Policy} is less susceptible to reverse causality (being constructed as a difference in air traffic levels for the same year), such concerns should be completely alleviated by using the average policy distortions among other cities within the same size group as excluded instruments.

B.3 Variable Construction: Predicted Policy Shock

Our aim is to quantify the distortions in air traffic induced by the CAB regulations at MSA level. We define the policy shock Δ_i^{Policy} impacting MSA i as the deviation in air traffic from market based levels during the pre-deregulation period. We construct it from the difference between the

[7] We thank an anonymous referee for suggesting this strategy.



Source: Authors' Calculations

Figure B2: Correlation between Predicted Distortions and Observed Changes in Air Traffic

Note: The plots display the link between the deregulation-induced changes in air traffic observed at city level, and the inferred policy distortions obtained from the data using the methodology described the Appendix. The magnitude of the regulatory distortions is determined at city level from the difference between the counterfactual level of air traffic in year 1977 had there not been any regulation in place, and the observed volume of air traffic in year 1977. Equation (13) in the Appendix formalizes this calculation.

counterfactual and the observed level of air traffic in year 1977.[8] Continuing with the notation introduced in the text of the paper, the policy distortion can be written as:

$$\Delta_i^{Policy} \equiv lnA^*{}_{i,1977} - lnA_{i,1977} = -\widetilde{\alpha}_i - \widetilde{\delta} lnZ_{it} \tag{14}$$

Of importance for such a calculation is the inference regarding the counterfactual air traffic level that would have been observed in the absence of market restrictions, $lnA^*{}_{i,1977}$. We rely on out-of-sample predictions generated from a reduced-form model of air traffic demand fitted on data generated in an environment of free market conditions.

We start by estimating the following regression in levels using MSA data from the post-deregulation period:

$$lnA_{it} = \alpha_i + \alpha_t + \beta_1 lnPop_{it} + \sum_k \beta_k \Big(\frac{Emp_{ikt}}{Emp_{it}}\Big) + \epsilon_{it} \tag{15}$$

where i, t and k indexes cities, years and sectors, respectively, and Emp stands for the employment level of a community. Given the available data, we use two time periods – 1983 and 1991 – which are sufficiently far apart in time to generate enough data variation to identify the model parameters while also controlling for city and time fixed effects.

By estimating equation (15), the goal is to use the resulting coefficients in combination with MSA level data for year 1997 to make out-of-sample predictions about the counterfactual unconstrained level of air traffic prior to deregulation, $lnA^*{}_{i,1977}$.

Getting consistent estimates in equation (15) is essential for the construction of the policy shock measure. Any biases such as, for example, biases induced by endogeneity or by omitted demand determinants, would lead to systematic miss-measurements in the counterfactual level of air traffic $lnA^*{}_{i,1977}$. In turn, this will affect in a non-random way the magnitude of the MSA level policy shock. For example, an upward bias in the estimated population coefficient $\hat{\beta}_1$ in equation (15) would make the policy shock measure Δ_i^{Policy} in equation (14) become a function of the size of an MSA through the term $(\hat{\beta}_1 - \beta_1) lnPop_{i,1977}$. Since our ultimate goal is to use the constructed policy shocks as instruments for air traffic in regressions examining MSA growth, the quality of our instrument is going to depend on how precisely we estimate the demand for air services.[9]

Equation (15) is estimated using city and time fixed effects indexed by α. The inclusion of fixed effects is very convenient as many cost determinants affecting air fares are either time specific (e.g., fuel, labor, capital costs) or location specific (e.g., geography). Conditional on prices, the main determinant of the demand for air services is population size.[10] To refine the model specification, we incorporate information on the intensity of travel demand by adding measures of industrial composition at MSA level, i.e., sector employment shares.

Since the population level is endogenous in the regression, we instrument for it using (decades long) lags of population in level and growth rates, as well as a constructed measure of lagged market potential. We define: $MktPotent_{it} = \sum_{s \neq i}(GDP_{st}/Dist_{is})$, with s indexing a geographical unit. Because of GDP data availability, we first construct market potential at county level, and then aggregate it across all the counties within an MSA to obtain the market potential of each city in

[8] We thank an anonymous referee for suggesting this strategy.

[9] It is important to mention here that all the model specifications of MSA growth estimated in the paper control for initial economic conditions, which include MSA characteristics in year 1977. However, this should not prevent us from doing diligent work ex-ante by constructing policy-based instruments for air traffic that are orthogonal to observable MSA characteristics.

[10] We have used per-capita income as determinant of air traffic demand at MSA level. However, once controlling for location and time fixed effects, the variable lost predictive power and statistical significance.

our sample.

Table B1: A Model of Demand for Air Services

	Number of Air Passengers$_{it}$		
	OLS	*2SLS*	1^{st} Stage
	(1)	(2)	(3)
Population$_t$	2.492^{**}	2.521^{**}	
	[0.477]	[0.780]	
Share Manufacturing$_t$	-0.03	-0.026	-0.074^{+}
	[0.228]	[0.226]	[0.045]
Share Services$_t$	-0.298	-0.292	-0.174^{**}
	[0.610]	[0.569]	[0.061]
Share Retail$_t$	0.556	0.566	-0.07
	[0.724]	[0.744]	[0.080]
Share Wholesale$_t$	0.041	0.041	0.005
	[0.466]	[0.465]	[0.031]
Share Transport/Utilities$_t$	0.252	0.254	-0.040^{+}
	[0.272]	[0.278]	[0.024]
Share Construction$_t$	0.015	0.016	0.016
	[0.181]	[0.180]	[0.023]
Lagged Population ($\approx$ t-30)			5.427^{**}
			[0.514]
Lagged Population Growth ($\approx$ t-20)			4.401^{**}
			[0.565]
Lagged Market Potential			0.295^{**}
			[0.103]
MSA Fixed Effects	yes	yes	yes
Year Fixed Effects	yes	yes	yes
Observations	518	514	514
R-squared	0.179	0.179	0.578
First Stage Stats:			
F statistic			46.40
Hansen J statistic		0.009	
Hansen p-value		0.995	

$^{**}p < 0.01$, $^{*}p < 0.05$, $^{+}p < 0.1$. Robust standard errors clustered at MSA level in brackets.

Notes: The reported results correspond to the regression equation (15) in this Appendix, which fits a model to explain the level of air traffic at MSA level during a period of fully deregulated aviation industry. The sample spans two years of data, 1983 and 1991, chosen distant apart so that there is sufficient variation in the variables of interest after including time and MSA fixed effects. Because the population level is endogenous in the model, it is instrumented by lagged values of population (level and growth rate) and market potential (calculated at MSA level). For year 1983, the lags correspond to years 1950 to 1960 for population, and 1970 for the market potential variable. For year 1991, the lags correspond to years 1960 to 1970 for population, and 1980 for the market potential variable. The IV estimates from the regression model are then used to construct out-of-sample predictions for the counterfactual level of air traffic in year 1977 had there been no CAB regulation (i.e., $lnA^{*}{}_{i,1977}$).

Table B1 reports the results from estimating equation (15). Column 1 reports the OLS coefficients and column 2 reports the 2SLS estimates, with column 3 providing the first stage results. One thing to notice is that there is not a large difference between the OLS and 2SLS coefficients, and this is not due to the selected set of excluded instrument. As observed from the first stage statistics reported at the bottom of the table, the excluded instruments perform well in that they are good predictors of population at MSA level and are not correlated with the residual variation in air traffic.

Combining the estimates from column 2 of Table B1 with MSA level data for year 1977, we construct out-of-sample predictions for what the level of air traffic would have been during the regulation period, had the CAB not been in place to impose market restrictions. That is, we predict $lnA^{*}{}_{i,1977}$ so that we can then apply equation (13) to construct Δ_i^{Policy}.

Table B2 reports the results from regressing the constructed policy shock Δ_i^{Policy} on pre-deregulation urban growth variables, such as population, income or employment growth. Column 6 of Table B2 also reports the regression of Δ_i^{Policy} on the post-deregulation air traffic changes. Interestingly, the policy shock constructed from out-of-sample predictions is not correlated with either of the dependent variables in our main regression models, however it is correlated with the endogenous change in air traffic at city level. This findings are useful in strengthening the validity of the proposed instrument.

Table B2: Understanding the Variation in the Policy Shock

	Dependent Variable: Predicted Policy Shock Δ_i^{Policy}					
	(1)	(2)	(3)	(4)	(5)	(6)
Population Growth (1969-1977)		0.004			-1.412	
		[2.617]			[3.763]	
Income Growth (1969-1977)			-4.188		-4.996	
			[2.978]		[3.165]	
Employment Growth (1969-1977)				-0.124	1.067	
				[1.619]	[2.468]	
Passenger Growth (1977-1983)						4.598**
						[0.483]
Medium City	0.156*	0.156*	0.141+	0.155*	0.149+	0.050
	[0.078]	[0.079]	[0.080]	[0.074]	[0.080]	[0.068]
Large City	0.497**	0.497**	0.468**	0.495**	0.476**	0.215**
	[0.065]	[0.064]	[0.070]	[0.069]	[0.074]	[0.061]
Observations	259	259	259	259	259	259
R-squared	0.179	0.179	0.183	0.179	0.184	0.438

$^{**}p < 0.01$, $^{*}p < 0.05$, $^{+}p < 0.1$. Robust standard errors clustered at MSA level in brackets.

Notes: The reported results are obtained from regressing the predicted policy shock Δ_i^{Policy} on the main urban growth indicators measured during the pre-deregulation period: population growth, income growth and employment growth. The last column also reports results from regressing Δ_i^{Policy} on the post-deregulation changes in air traffic at city level. All regressions are estimated using cross-sectional data, so no city or time fixed effects are necessary. The only controls included in all the regressions are indicators for the size category of the sampled cities, with small cities being the omitted group.

B.4 Estimation Results: Policy Distortion Inferences based on the Residual Variation in Air Traffic

To reinforce the evidence of a causal effect of air services on the economic growth of local communities, we experiment with a second set of instruments. We make inferences about the magnitude of the regulatory distortions affecting city level air traffic by comparing actual air passenger flows in year 1977 to out-of-sample predictions for what the level of air traffic would have been that year absent any market regulations. Equation (13) provides details on the construction of the policy distortion instrument, Δ_i^{Policy}.

We estimate the same regression model as reported in the paper (i.e., regression equation (6) in the main text), but on a slightly modified data sample. Since the policy distortion instrument has no time dimension – it is constructed as a one-time location-specific shock – we only use cross-sectional data from the post-deregulation period. A consequence of this sample change is that now we cannot control for unobservable location characteristics using city fixed effects. While this may seem like a limitation of the estimation procedure, note that the proposed instrument is defined as a difference, so, by construction, Δ_i^{Policy} is purged of city-specific effects.

Another sample modification is a shift in the post-deregulation time window from the period 1977-1991 to the period 1983-1997. We make this change to avoid an overlap between the period over which urban growth rates are constructed, and the post-deregulation period over which the policy-induced air traffic changes are measured. This ensures that there is no possibility for unobservable factors that simultaneously affect air traffic and urban growth rates during the period 1983-1997, to also determine the variation in Δ_i^{Policy}.[11]

Table C3 reports the new set of results with population, per-capita income, and employment growth, respectively, as economic outcomes to be explained. For each dependent variable, the first set of estimates reports the OLS results as reference, the second set reports the IV estimates with Δ_i^{Policy} as the only exogenous instrument for the growth in air traffic, and the third set reports the IV estimates with the policy distortion Δ_i^{Policy} allowed to vary by city size group.

Focusing on the results for population growth, one thing to notice is the similarity between the OLS coefficient on air traffic growth and the corresponding panel data estimate from column 4 in Table 3 in the paper. Surprisingly, the 2SLS results reported in columns 2-3 differ from prior findings in that they are not statistically significant, and with magnitudes very close to zero. From the first stage estimates reported at the bottom of the table, it does not seem that the instruments are the ones responsible for the lack of significant effects. The policy distortion variable and its interaction terms enter with the correct sign and are high significant, which explains the large F-statistic in the first stage. When using multiple instruments, we also test for exclusion restrictions and find, based on the Hansen J-statistic, that the constructed instruments are indeed exogenous to the regression model. While it is not clear what explains the insignificant estimates, one possibility could be the limited variation in the growth rate of population over the period 1983-1997 that is left to be explained by the instrumented air traffic growth rate.

Moving on to the estimates for per-capita income growth, these are reported in columns 4-6 of Table C3. This time, the OLS coefficient for the growth rate of air traffic is smaller in magnitude compared to the corresponding estimate from column 2 of Table 4 in the paper. Again, it is possible that the variation in urban growth rates over the period 1983-1997 is not as large as in the panel data sample because of the lack of time variation. However, the IV estimates reported in columns 5 and 6 are significant and much larger in magnitude that the OLS result. Like before, a plausible explanation for this direction of change is the disproportional allocation of transportation services to slow income growing cities during the regulatory period.[12]

Most of the observations regarding the income growth estimates apply equally well to the results obtained from the employment growth regressions. These are reported in columns 7-9 in Table C3 Focusing on the OLS coefficient from column 7, we notice again that its magnitude is smaller compared to the corresponding coefficient from column 5 of Table 4 in the paper. However, once we correct for endogeneity using instrumental variables, the magnitude of the coefficients rises to a level that is only slightly larger than prior OLS estimates. As before, the excluded instruments perform well in that they are highly correlated with the endogenous air traffic growth variable, as indicated by the large F statistics, and they are uncorrelated with the urban growth residual, as suggested by the Hansen J test for overidentifying restrictions.

[11]Instrumental variables estimates obtained based on city growth rates calculated over the period 1977-1997 are qualitatively similar to the reported estimates and are available upon request.

[12]Interesting enough, the IV estimates are almost identical in magnitude to the panel OLS estimates. This could be taken as suggestive evidence that much of the endogeneity between air traffic and urban growth rates has been removed by double differencing the data.

B.5 Additional Robustness Exercises

One robustness check that we perform but do not report in the paper investigates an alternative mechanism that could match our findings. Communities that benefit from an exogenous positive shock to income growth in the post-deregulation period are likely to generate both an increase in the demand for consumption goods, which triggers employment growth in retail sectors, as well as an increase in the spending on air travel services (considered luxury goods). Of course, such a scenario must happen systematically across the cities in our sample to explain the positive and significant results that we have repeatedly found so far. However, communities in the close proximity of large urban areas may be a case in point. Economic geography forces, such as, market and supplier access, could provide reasons for why these locations may experience positive income shocks, and also be strategic locations for service or retail establishments. If these positive income shocks also determine the consumers in these locations to enjoy more air travel, then the effect of air traffic on urban growth must be larger for the communities located in the vicinity of large urban areas. Table C4 reports the results from a specification augmented with an interaction term between the city level air traffic growth rate and an indicator for small or medium sized MSAs located within 150 miles of a large urban area. In all specifications the sign of the interaction term is negative, although only at times significant - opposite from our proposed hypothesis. We take the reported results as partial evidence to suggest that proximity to large cities makes population and employment growth in small communities less responsive to changes in air passenger traffic.

C Table Appendix

Table C1: First Stage Regressions
(corresponding to the 2SLS estimations reported in Table 6 in the paper)

Dependent Variable:	**Air Passenger Growth Rate** $_{iT}$			
	(1)	(2)	(3)	(4)
Excluded Instruments:				
Time × Medium City	0.014+			
	[0.008]			
Time × Large City	0.058**			
	[0.009]			
Avg. Passenger Growth in *other* Cities,		0.832**		0.577**
by Size		[0.115]		[0.160]
Avg. Passenger Growth in *other* Cities,			6.315**	3.349*
by Location and Size			[1.028]	[1.359]
Passenger per capita$_{t_0}$	-0.075**	-0.076**	-0.075**	-0.075**
	[0.015]	[0.015]	[0.016]	[0.015]
Population$_{t_0}$	-0.035	-0.037	-0.113+	-0.074
	[0.064]	[0.064]	[0.061]	[0.063]
Population Lag$_{t_0-10}$	-0.017	-0.016	0.015	-0.006
	[0.016]	[0.017]	[0.020]	[0.018]
Population Lag$_{t_0-20}$	0.019	0.021	0.019	0.016
	[0.023]	[0.022]	[0.021]	[0.021]
Population Lag$_{t_0-30}$	0.007	0.007	0.004	-0.000
	[0.023]	[0.023]	[0.023]	[0.022]
Income per capita$_{t_0}$	-0.142**	-0.145**	-0.119*	-0.127*
	[0.055]	[0.055]	[0.055]	[0.054]
Employment$_{t_0}$	0.125**	0.124**	0.107*	0.125**
	[0.047]	[0.048]	[0.044]	[0.046]
Share Manufacturing$_{t_0}$	-0.024+	-0.024+	-0.015	-0.019
	[0.014]	[0.014]	[0.013]	[0.014]
Share Services$_{t_0}$	0.023	0.024	0.047+	0.030
	[0.029]	[0.029]	[0.028]	[0.028]
Share Retail$_{t_0}$	0.077	0.077	0.080+	0.077
	[0.048]	[0.049]	[0.047]	[0.047]
Share Wholesale$_{t_0}$	-0.014	-0.015	-0.021*	-0.016+
	[0.010]	[0.011]	[0.009]	[0.009]
Share Transport/Utilities$_{t_0}$	0.001	0.001	0.018	0.009
	[0.016]	[0.016]	[0.018]	[0.017]
Share Construction$_{t_0}$	-0.018+	-0.018+	-0.025*	-0.021*
	[0.011]	[0.011]	[0.010]	[0.010]
Time Fixed Effects	yes	yes	yes	yes
MSA Fixed Effects	yes	yes	yes	yes
Observations	520	520	520	520
R-squared	0.778	0.774	0.768	0.780
First Stage Statistics:				
F-statistic	30.11	52.39	37.75	33.47
Partial R-squared	0.173	0.156	0.133	0.179

$^{**}p < 0.01$, $^{*}p < 0.05$, $^{+}p < 0.1$. Robust standard errors in brackets.

Table C2: First Stage Regressions
(corresponding to the 2SLS estimations reported in Table C3 in this appendix)

Dependent Variable:	**Air Passenger Growth Rate** $_{iT}$	
	(1)	(2)
Excluded Instruments:		
Policy Distortion ($\hat{\Delta}^{Policy}$)	0.063**	0.077**
	[0.010]	[0.013]
Policy Distortion ($\hat{\Delta}^{Policy}$) $\times$ Medium City		-0.034*
		[0.017]
Policy Distortion ($\hat{\Delta}^{Policy}$) $\times$ Large City		0.015
		[0.024]
Poulation level$_{t_0}$	-0.013	-0.011
	[0.016]	[0.015]
Population Growth Lag$_{t_0-10}$	1.268**	1.442**
	[0.335]	[0.327]
Population Growth Lag$_{t_0-20}$	0.099	0.120
	[0.197]	[0.202]
Population Growth Lag$_{t_0-30}$	0.036	0.085
	[0.170]	[0.184]
Income per capita$_{t_0}$	-0.023	-0.014
	[0.025]	[0.025]
Employment level t	0.022	0.016
	[0.016]	[0.015]
Share Manufacturing$_{t_0}$	-0.014	-0.017+
	[0.009]	[0.010]
Share Services $_{t_0}$	-0.007	-0.015
	[0.017]	[0.018]
Share Retail t	0.007	0.001
	[0.022]	[0.024]
Share Wholesale$_{t_0}$	-0.010	-0.007
	[0.008]	[0.008]
Share Transport/Utilities$_{t_0}$	0.003	0.002
	[0.009]	[0.009]
Share Construction$_{t_0}$	0.025**	0.025**
	[0.008]	[0.007]
MSA Size Fixed Effects	yes	yes
Observations	259	259
R-squared	0.621	0.641
First Stage Statistics:		
F-statistic	46.15	24.58
Partial R-squared	0.32	0.36

$^{**}p < 0.01$, $^{*}p < 0.05$, $^{+}p < 0.1$. Bootstrapped standard errors (500 replications) in brackets.

Table C3: Instrumental Variables Estimates for the Effect of Air Travel on Economic Growth (1983-1997)

	Dependent Variable: Annual Growth Rate$_{iT}$								
	Population			***Income***			***Employment***		
	OLS	*2SLS*	*2SLS*	*OLS*	*2SLS*	*2SLS*	*OLS*	*2SLS*	*2SLS*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Passenger Growth Rate$_{iT}$	0.035**	0.006	0.0001	0.016^{+}	0.032**	0.035**	0.046**	0.055**	0.058**
	[0.011]	[0.021]	[0.020]	[0.009]	[0.015]	[0.016]	[0.014]	[0.022]	[0.023]
MSA Size Fixed Effects	yes	yes	yes	yes	yes	yes	yes	yes	yes
Initial Economic Conditions $_{(T_0)}$	yes	yes	yes	yes	yes	yes	yes	yes	yes
Pop. Lags $_{(T_0-10, T_0-20, T_0-30)}$	yes	yes	yes	yes	yes	yes	yes	yes	yes
Sectoral Composition	yes	yes	yes	yes	yes	yes	yes	yes	yes
Observations	261	259	259	261	259	259	261	259	259
R-squared	0.516	0.533	0.526	0.350	0.332	0.327	0.456	0.470	0.469
Excluded Instruments:									
Policy Distortion ($\widehat{\Delta}^{Policy}$)		0.063**	0.077**		0.063**	0.077**		0.063**	0.077**
		[0.010]	[0.013]		[0.010]	[0.013]		[0.010]	[0.013]
Policy Distortion × Med. City			-0.034*			-0.034*			-0.034*
			[0.017]			[0.017]			[0.017]
Policy Distortion × Lg. City			0.015			0.015			0.010
			[0.024]			[0.024]			[0.024]
First Stage Statsistics:									
F-statistic		46.15	24.58		46.15	24.58		46.15	24.58
Hansen J statistic		n.a.	1.493		n.a.	0.974		n.a.	0.370
Hansen J p-value		n.a.	0.474		n.a.	0.614		n.a.	0.831

$^{**}p < 0.01$, $^{*}p < 0.05$, $^{+}p < 0.1$. In brackets, robust standard errors for OLS specifications, and bootstrapped standard errors (500 replications) for 2SLS estimations.

Notes: The reported results correspond to the main regression equation in the paper (i.e., equation (6)) estimated using instrumental variables and cross-sectional data from the post-deregulation period. The dependent variables measuring urban growth are calculated at city level over the interval 1983-1997. The variable of interest, i.e., air passenger annual growth rate, is calculated over the period 1977-1983. The excluded variables used as instruments for the growth rate of air traffic capture the extent of regulatory distortions at city level. The policy distortion variable is constructed based on equation (13) in the Appendix, and consists of the difference between the counterfactual level of air traffic in year 1977 had there not been any regulation, and the actual level of air traffic observed in that year. The complete list of control variables and fixed effects from prior estimations are included, except for the city fixed effects which are now replaced by the city size category fixed effects.

Table C4: Robustness Check - Effect of Proximity to Large Airport Hubs for Small and Medium Size Cities

	Dependent Variable: Annual Growth Rate for...								
	Population			*Income*			*Employment*		
	OLS	*2SLS*	*2SLS*	*OLS*	*2SLS*	*2SLS*	*OLS*	*2SLS*	*2SLS*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Passenger Growth Rate$_{iT}$	0.034**	0.086**	0.097**	0.035**	0.067**	0.089**	0.057**	0.107**	0.109**
	[0.008]	[0.019]	[0.021]	[0.009]	[0.019]	[0.021]	[0.014]	[0.030]	[0.031]
× I(Dist<150 & MSA≠ Large)	-0.010	-0.031*	-0.035*	-0.006	-0.020	-0.037**	-0.010	-0.035+	-0.030
	[0.009]	[0.015]	[0.017]	[0.009]	[0.014]	[0.013]	[0.017]	[0.021]	[0.023]
MSA Fixed Effects	yes	yes	yes	yes	yes	yes	yes	yes	yes
Time Fixed Effects	yes	yes	yes	yes	yes	yes	yes	yes	yes
Base Year Controls	yes	yes	yes	yes	yes	yes	yes	yes	yes
Pop. Lags$_{(T_0-10,T_0-20,T_0-30)}$	yes	yes	yes	yes	yes	yes	yes	yes	yes
Sectoral Composition	yes	yes	yes	yes	yes	yes	yes	yes	yes
Observations	524	520	520	524	520	520	524	520	520
R-squared	0.674	0.613	0.584	0.918	0.912	0.901	0.755	0.741	0.739
Excluded Instruments:									
Time × Medium City		yes			yes			yes	
Time × Large City		yes			yes			yes	
Pax Growth in *other* Cities by Size			yes			yes			yes
Pax Growth in *other* Cities by Loc. & Size			yes			yes			yes

$^{**}p < 0.01$, $^{*}p < 0.05$, $^{+}p < 0.1$. Robust standard errors clustered at MSA level in brackets.

Notes: The reported estimates correspond to the main regression equation in the paper (i.e., equation (6)), which is augmented with information on economic geography. The variable *I(Dist<150 & MSA≠ Large)* is an indicator variable equal to one if a small or medium size city lies within 150 miles from a medium or large hub airport as classifies by the Federal Aviation Administration. Its interaction with the variable of interest identifies any differential responses of smaller communities to changes in air passenger growth determined by their proximity to main national airports. To remove endogeneity concerns, for the reported 2SLS estimates in columns 2, 5, and 8, the growth rate of air traffic is instrumented by the same excluded variables as those reported in column 1 of Table 5 in the paper. Furthermore, for the reported 2SLS estimates in columns 3, 6, and 9, the growth rate of air traffic is instrumented by the same excluded variables as those reported in column 4 of Table (5) in the paper. The complete list of the controls and fixed effects from prior estimations are included in all the reported specifications.