HETEROGENEOUS LOCAL FISCAL MULTIPLIERS: NEW SHIFT-SHARE EVIDENCE FROM THE UK

Julio Brandao-Roll
LSE*

Abstract

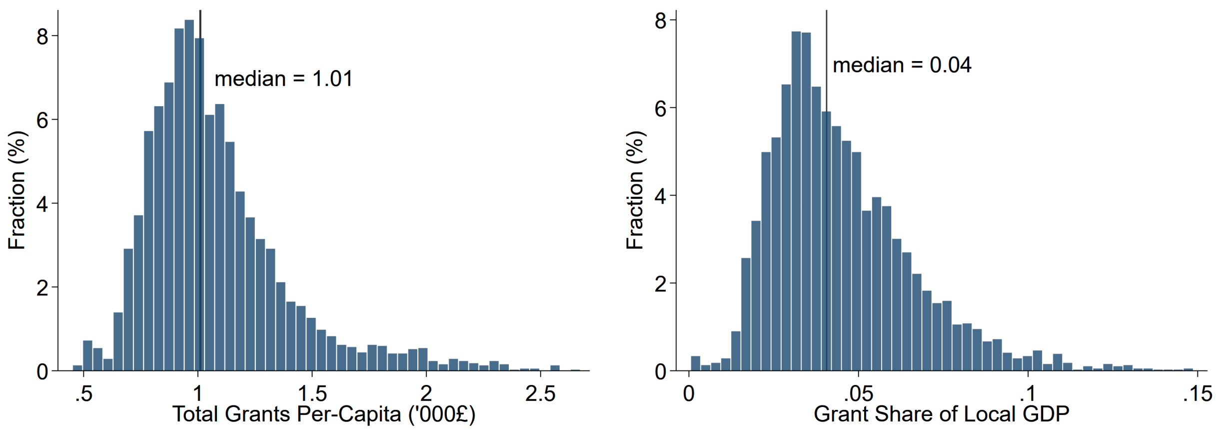
This paper shows evidence and explains heterogeneity in local fiscal multipliers that is unrelated with differences in local marginal propensities to consume. Instead, local labor market and demographic characteristics play a key role. First, I present evidence from the UK of an average local multiplier of 1.69 and 1.71 for services and capital spending, respectively, using a shift-share IV design leveraging UK councils' reliance on funds from the central government. There are, however, significant inter-council differences in the multiplier which can be explained by workers' skill level and labor inactivity. I further show that this novel heterogeneity cannot be explained by variation in local MPCs and that local spending boosts worker productivity while also improving local social and health conditions. I rationalize these results with a model of heterogeneous labor and productivity shocks that impose a psychological toll to workers' cognitive load capacity. Results show potential gains from removing fiscal misallocation between councils and optimal fiscal policy.

1 Introduction

Fiscal policy discussions usually revolve around precise estimates of the fiscal multiplier, particularly whether it is above or below one. Since the Great Recession, however, the literature on national multipliers has done significant work analyzing the variability of estimates and their state-dependence. The literature on local fiscal multipliers, on the other hand, has paid less attention to multiplier heterogeneity at the local level. This is possibly because local estimation procedures do away with aggregate-level channels (e.g. monetary policy), whose effect on the fiscal multiplier is more well known. Identifying local multiplier variation, however, is important since local spending decisions, for instance whether a council should go through a fiscal expansion or contraction, can change significantly between councils if multipliers differ. It is, then, worthwhile to assess whether we have local heterogeneity in the fiscal multiplier and identify the drivers of such local

*Contact: j.brandao-roll@lse.ac.uk. Web: https://www.juliobrandaoroll.com/. I am particularly indebted to Xavier Jaravel and Maarten De Ridder for extensive advice and comments. I also thank Felipe Bordini, Will Matcham, Ben Moll, Damjan Pfajfar, Derek Pillay, and seminar participants at the LSE and at the ASPEC 2022 conference for comments.

Figure 1: *LAD Distribution of Per-Capita Grant Awards and Grant Share of Local GDP*



variation.

To address this question, I take advantage of the unique fiscal setting in the UK. Local government (called councils or local authority districts, or LADs) service and capital spending in the UK is a significant share of total public spending (approximately 13% for the fiscal year ending in 2020 according to the Office for National Statistics, or ONS). Importantly, fiscal transfers are but a small part of total LAD spending (approximately 0.2% of local net current expenditure) so virtually all local spending is in the provision of a public good. LADs have different sources of funding, of which central government grants are a significant share. Changes to these grants affect local authorities differently as their reliance on different sources of revenue varies from one another. I show the distribution of grant awards per-capita and the grant share of local GDP in Figure 1 for the LAD-year pairs between 2009 and 2019. Clearly there is significant variation in grant award and reliance between local governments.

I leverage this variation in the reliance on central government grants at the council-level to identify the effect of local government spending on local GDP. Using a shift-share design, I find evidence of a positive average, short-term local fiscal multiplier of 1.69 for local government services and a multiplier of 1.71 for capital spending. Results are robust to controlling for local-level parameters, changes to the specification and the SSIV structure, and to running the estimation at the commuting zone level. I find no evidence of a statistically significant employment multiplier even though local authorities can use the additional funding to hire labor directly. To identify the fiscal multiplier estimate, I rely on the exogeneity of the one-year lagged central government grant share of local GDP to deal with the standard endogeneity issue in estimating fiscal multipliers. Although we cannot verify this exogeneity directly, I show evidence of its validity via recommended falsification tests.

I then characterize the heterogeneity in the fiscal multiplier with respect to local labor market and demographic parameters. Results can be divided into two groups. In the first one, higher economic inactivity per-capita and a higher low-skill labor share decrease the service and capital spending fiscal multipliers, respectively. In the second one, having more people in inactivity who want a job and higher anxiety levels in the population increase the multiplier. This variation due to local heterogeneity is significant as local estimates can vary between 0.6 and 3 if local observables change by one standard deviation. I further present evidence that this variation cannot be explained by local heterogeneity in marginal propensities to consume (MPCs), especially since I do not observe multiplier variation due to variables closely related to MPCs such as child poverty and inequality. Moreover, I find that local spending is able to boost worker productivity while improving local social and health conditions. On heterogeneity due to type of spending, I show that the average fiscal multiplier is mainly driven by spending in social care.

These results indicate two things. First, that local-level characteristics are important factors in determining the effectiveness of fiscal policy in increasing GDP. Second, that social-care spending plays an important role in the mechanism behind the above-one multiplier. Optimal policymaking should, then, take into account local conditions in determining the councils in need of a fiscal expansion or contraction.

To be able to assess fiscal policy, I construct a model using one possible mechanism that can explain both the local multiplier heterogeneity and the role of social-care. Taking a cue from the economics and psychology literatures, I assume high and low-skilled workers are subject to a low mental bandwidth shock that lowers their cognitive aptitude and, hence, their productivity. This shock represents all ways through which a person's cognitive load may be overtaxed, for example through poverty and sickness. Workers can return to their normal productivity level once hit by a high bandwidth shock which depends on public spending. Moreover, workers can be of high-risk type which captures less revertible shocks such as suddenly becoming a carer for a partner with a long-term condition. I assume public spending is less effective for high-risk individuals in bringing them back to their healthy, more productive state. Applying this model to places with different low-bandwidth shock rates, shares of high-skilled labor, and shares of high-risk individuals I am able to reproduce the observed heterogeneous trends in the fiscal multiplier. Results are intuitive: public spending is most effective when helping high-skill (i.e. most productive) workers who are not high-risk individuals return to their healthy state. To the best of my knowledge, this is the first paper that links the effect of individual-level cognitive bandwidth capacity to the effectiveness of fiscal policy.

I then analyze potential gains from optimal fiscal policy. I split the analysis into two parts. In the first one, I show that by taking local heterogeneity in the multiplier into account, we can derive gains from current local fiscal policy in the UK even if we keep total spending constant. This is due to *fiscal misallocation*, i.e. the fact that high-multiplier councils do not receive the largest central government grant awards. While this misallocation declined between 2010 and 2019 in the UK, cumulative results are significant. If the central government had optimally awarded grants between 2010 and 2019, i.e. more grants to councils with high multipliers, it would have generated an extra 57.9 billion pounds in real terms. Conversely, if we assume the national government could control local budgets altogether (vs. only the grant allocation) then removing fiscal misallocation entirely since 2010 would have resulted in an extra 156 billion pounds, or 19.2% of the central government budget in 2019. These results highlight the importance of taking heterogeneity into account for fiscal policy.

In the second part, I present the social planner's optimal fiscal policy and compare it with actual spending by UK councils. Results have two main takeaways. First, there is considerable optimal spending heterogeneity between councils as the interquartile range for the ratio between optimal and actual spending is 0.84. Second, a social planner would want, on average, to increase local budgets by 28%, a result that reflects the 1.69 baseline fiscal multiplier estimate. I show then that the potential gains from adopting the planner's fiscal policy have increased over time, averaging 0.5 percentage points of GDP per-capita yearly and 0.65 percentage in 2019. The latter would raise the 2019 GDP per-capita growth rate in the UK by more than 50%.

Related Literature

This paper relates to different strands of literature. On the state-dependency of local multipliers, Basso and Rachedi (2021) find evidence in the US that a higher share of young people in the population increases the fiscal multiplier of military spending. They rationalize results in a New Keynesian framework with credit market frictions. Similarly, Morita (2022) is a recent attempt[1] at explaining low fiscal multipliers in Japan with the ageing of its population, now from a VAR-narrative perspective. Finally, Brandao-Roll, Ridder, Hannon and Pfajfar (2024) show local heterogeneity of multipliers from Pell Grants with respect to recessions and local type of college. I make two important additions to these results. First, I show further evidence of labor-market and demographic-driven local multiplier heterogeneity. Second, I propose a simple model that rationalizes

[1] Building on Yoshino and Miyamoto (2017).

results on local heterogeneity which does not require a New Keynesian framework to explain variation in the local fiscal multiplier.[2]

On the literature on local fiscal multiplier estimates, Chodorow-Reich, Feiveson, Liscow and Woolston (2012), Fishback and Kachanovskaya (2015), and Auerbach, Gorodnichenko, McCrory and Murphy (2022)[3] provide different estimates for the local multiplier in the US, particularly during downturns. These papers, however, do not analyze the effects of state-dependency at the local level which is my focus. There is evidence, on the other hand, that local fiscal multipliers estimates are larger during recessions relative to expansions (Nakamura and Steinsson, 2014, Shoag, 2016, Berge, De Ridder and Pfajfar, 2021). I expand this result on two fronts. First, I show that local public spending is also state-dependent relative to local area characteristics. I then propose a mechanism to rationalize my empirical findings that makes use of individual-level cognitive load capacity. It is important to notice that a large part of the literature on multipliers deals with the effect of direct transfers and/or purchases by governments. In my case, local authority spending in the UK is virtually all about the provision of services and capital. As such, the patterns of heterogeneity that I highlight along with the mechanism I propose do not involve heterogeneity due to variation in local MPCs, which is usually the explanation behind business cycle variation in multipliers from fiscal transfers.

On the aggregate level, there is significant evidence of fiscal multiplier heterogeneity. Different authors have shown state-dependence of multipliers regarding interest rates (Christiano, Eichenbaum and Rebelo, 2011, Ramey and Zubairy, 2018), expansions and contractions (Auerbach and Gorodnichenko, 2012), exchange rate regime, debt level, and trade openness (Ilzetzki, Mendoza and Végh, 2013, Corsetti, Meier, Müller and Devereux, 2012). There is also evidence that fiscal multipliers from changes in spending and taxes are different (Caldara and Kamps, 2017), along with variation due to methodological choice (Gechert, 2015, Capek and Crespo Cuaresma, 2020). Finally, there is work regarding heterogeneity with respect to spending type (Pappa, 2009, Boehm, 2016).[4] While the aggregate multiplier literature paints a rich picture vis-a-vis the variation in estimates, less is known at the local level. I intend to show that we also observe significant heterogeneity in local-level estimates which is not due to the usual channels analyzed at the aggregate level. Local-level heterogeneity has to rely on a micro-level mechanism, of

[2] C.f. Muratori, Juarros and Valderrama (2023) for evidence on multiplier heterogeneity due to differences in government purchases, and Gibbons, Lyytikäinen, Overman and Sanchis-Guarner (2019) and Gibbons and Wu (2019) for analyses on the differential impact of road and airport infrastructure investments, respectively.

[3] See Chodorow-Reich (2019) for an interesting review of local fiscal multipliers.

[4] C.f. Ramey (2019) for a more extensive review.

which I show evidence.

Finally, I take inspiration from the literature at the intersection of psychology and economics on the psychological toll to one's mental bandwidth. Schilbach, Schofield and Mullainathan (2016) is an interesting summary of how poverty, by imposing a cognitive load, can tax a person's bandwidth resulting in lower productivity and changes to rational behavior. Kaur, Mullainathan, Oh and Schilbach (2021) show evidence from a field experiment that increasing cash-on-hand raises the productivity of poor workers. Similarly, Schultz and Edington (2007) review results showing the toll of poor health on worker performance.[5] I expand these results by linking the low-bandwidth toll to fiscal policy as a mechanism that creates heterogeneity in the local fiscal multiplier depending on the local conditions of individuals. I also show direct evidence that fiscal policy both boosts worker productivity and improves local social and health conditions, results that can be naturally linked via the low-bandwidth mechanism.

The remainder of the paper is organized as follows. Section 2 describes the data. Section 3 describes the shift-share design that I use in order to calculate estimates. Section 4 presents my empirical results. Section 5 rationalizes results via a theoretical model and compares actual with optimal spending. Finally, Section 6 concludes.

2 Data

I rely on several council-level sources to pin-down the effect of local characteristics on local fiscal multipliers. The main public budget data comes from the ONS which has local public accounts information for England since the fiscal year of 2007-2008. These accounts hold information about service and capital expenditure on education, transportation, social care, healthcare, housing, cultural and environmental activities, law enforcement, planning and development, and general expenses. As the data covers the UK fiscal year which goes from April to March of the following year, I adjust all variables to match the chronological year.

Local authority data are also adjusted to account for differences in service provision between counties and districts. LADs can be categorized as metropolitan districts, London boroughs, unitary authorities, districts, and councils. For our analysis, it is important to note that non-metropolitan districts are part of a larger county.[6] Both of these

[5]See Burton, Chen, Schultz and Edington (2001) for evidence on allergies, Burton, Morrison and Wertheimer (2003) on the positive effect of drugs on the productivity of sick workers, and Goetzel, Ozminkowski, Hawkins, Wang and Lynch (2004) on the costs of presenteeism.

[6]For example, the district of Cambridge is within the council of Cambridgeshire.

local entities split the scope of local service that they provide: for instance, while non-metropolitan districts run environmental services, the encompassing council is responsible for social care. As councils receive central government grants for services provided in all of their districts, this creates a problem not only for the identification of the fiscal multiplier but also of cross-correlation between observations. To deal with the former, I split a council's spending and grants between its districts according to their population shares within the council. I then exclude LADs that are councils from the sample. As for the cross-correlation between non-metropolitan districts within the same council, I cluster standard-errors by their parent council if they are districts.

Although councils help administer the majority of the welfare-related direct transfers in the UK, they are not directly responsible for such programs. Those transfers are classified as either mandatory or discretionary. The former, such as Housing Benefit (now called Universal Credit), is set and paid by the central government, while the latter is funded by local authorities (with some help from the central government) usually as an additional benefit in case a household requires further assistance. Discretionary transfers are but a small part of total LAD spending (approximately 0.2% of local net current expenditure). Hence, most of councils' public spending is in the form of government services. I also include data from the local authority capital accounts which relate to investments in fixed assets.

Local authority accounts also show the sources of funding through local taxes and central government grants. LADs in the UK can generate revenue via Council Tax, which is a property tax levied on residential properties, Business Rates, a property tax on businesses, central government grants, and local fees and fines. Council tax rates are set up by LADs, but from 2012 to 2018 they could not be raised more than 2% for most councils without a public referendum. Business rates are set up by the central government but since 2013 local authorities get to retain 50% of what they collect locally, while the other half is redistributed back to councils as a grant. Prior to 2013, the central government decided the redistribution of 100% of the business rate income. Finally, central government grants are funded by the national government and can be of two types: general grants, which can be used freely by the LADs though could be for a specific spending category such as education, and earmarked grants, where the LAD only acts as a "middle-man" by transferring the grant funds either to people or to a third-party who runs a specific service. The most relevant general grants are called Specific Grants Within the AEF (Aggregate External Finance), which is an umbrella for several smaller grants, Formula Grants, and Revenue Support Grants. Earmarked grants are called Specific Grants Outside the AEF. For the shift-share approach, we will use data on non-earmarked grants as earmarked ones are mainly for mandatory rent rebates (i.e. transfers) and, hence, do not relate to service spending.

Aside from local government spending, I use several local-level controls and auxiliary variables. Council-level demographic data come from the ONS and the National Archive. Labor market data are from the Annual Population Survey. Local political control data come from the Open Council Data UK. Finally, aggregate disease levels were measured using the DALY (disability-adjusted life year) available from the IHME (Institute of Health Metrics and Evaluation). This is a measure of aggregate disease burden defined as the sum of the number of years lived with a disability and the number of years lost due to early death calculated using life expectancy. To focus on disease factors that are more closely related to local public health and social-care, I restrict the DALY to health changes due to risk factors which include environmental and occupational risks, behavioral risks (e.g. malnutrition), and metabolic risks (e.g. high cholesterol). Although not without its flaws, the DALY is an important measure in the public health literature which allows policymakers to compare, on the aggregate level, different disease risks by their impact on the population. I show in Table A.1 in the Appendix the summary statistics for the main variables of interest.

3 Research Design: The Shift-Share Approach

The identification strategy exploits the heterogeneous reliance of local councils on central government grants to pin-down the local fiscal multiplier and its heterogeneity due to variation in local characteristics. The fiscal policy setting in the UK creates a framework where central government transfers to local governments affect each council differently depending on their reliance on these funds. Hence, I propose a shift-share IV approach to deal with the usual endogeneity issue in estimating the impact of public spending on local GDP.

A Bartik-style instrument exploits how an aggregate shock affects local areas differently through variation in local shares. In this case, I rely on how changes to central government grants at the national level affect local councils differently given their heterogeneous exposure to grants measured via the council-level grant-to-GDP share. I follow the "shares-approach" framework developed by Goldsmith-Pinkham, Sorkin and Swift (2020) where the identification strategy relies on the exogeneity of the lagged grant shares conditional on observables. As such, consistency lies on exogenous exposure to common shocks. The main assumption behind a shares-based approach is that past exposure to a policy (i.e. the grant share of local GDP) is conditionally exogenous to growth in local

GDP.

Formally, for council l at time t I estimate the local fiscal multiplier as follows:

$$\frac{Y_{l,t+1} - Y_{lt}}{Y_{l,t-1}} = \beta \frac{G_{lt} - G_{l,t-1}}{Y_{l,t-1}} + \gamma X_{l,t-1} + \phi_l + \psi_t + \epsilon_{lt} \tag{1}$$

where Y_{lt} is real GDP level per capita at the council-level, G_{lt} is the local government real net spending per capita, $X_{l,t-1}$ are lagged controls, ϕ_l are council fixed-effects, ψ_t are year fixed-effects, and ϵ_{lt} is the residual. I opt for local GDP growth one period ahead to avoid issues with fiscal year reporting since local authority accounts are reported for periods between April and March of the following year. However, for β to have a direct fiscal multiplier interpretation, I scale both the dependent variable and the main regressor by the same variable $Y_{l,t-1}$.

Given the counter-cyclical nature of local spending, the OLS estimate of β is biased. To address this endogeneity issue, I instrument local government spending growth with the shift-share IV B_{lt} defined as:

$$B_{lt} = \sum_k g_{kt} s_{lk,t-1} \tag{2}$$

where $s_{lk,t-1}$ is the share of funding source k in the l council's GDP at time $t-1$ and g_{kt} is the national growth rate of funding k at time t. To be clear, if the central government offers funding to councils through two types of grants ($k = 1, 2$), the share $s_{1,10,0}$ is the share of grant 1 in council 10's local GDP at time 0 and $s_{2,10,0}$ is the share of grant 2. Identification comes from the exogeneity of $s_{lk,t-1}$ with respect to changes in local GDP.

Formally, the "shares-approach" for identification in a shift-share estimation requires both relevance and validity conditions to hold. Following Goldsmith-Pinkham et al. (2020), for T time periods, K grants, and L councils, the difference between the 2SLS estimator and the parameter of interest is:

$$\hat{\beta} - \beta = \frac{\sum_{t=1}^{T} \sum_{k=1}^{K} g_{kt} \sum_{l=1}^{L} s_{lk,t-1} \epsilon_{lt}^{\perp}}{\sum_{t=1}^{T} \sum_{k=1}^{K} g_{kt} \sum_{l=1}^{L} s_{lk,t-1} \Delta G_{lt}^{\perp}} \tag{3}$$

where ΔG_{lt} is the change in local fiscal spending scaled by lagged local GDP (as shown in Equation 1) and the $\perp$ superscript indicates the corresponding residualized variable after controlling for $X_{l,t-1}$ and the fixed-effects.

The relevance condition requires that the denominator in Equation 3 must converge to a non-zero value, i.e. that the grant shares hold predictive power over the local spending growth ΔG_{lt} conditional on controls and that the aggregate growth rates g_{kt} do not weight the covariates in a way that the sum cancels out. This is easily verified by regressing local spending growth on the instrument.

As for the validity condition, we require that the numerator in Equation 3 must converge to zero. This happens when the grant shares are uncorrelated with the error term conditional on the controls, i.e. when $\mathbb{E}[\epsilon_{lt} s_{lk,t-1} | X_{l,t-1}, \phi_l, \psi_t] = 0$ for all k where $g_{kt} \neq 0$. The assumption of grant share exogeneity rests on the idea that councils that rely on the central government for funds with different intensities are differently exposed to policy shocks affecting local grants. This is akin to a difference-in-differences counterfactual: in the absence of aggregate shocks to central government grants, high and low-dependent councils would have behaved similarly in terms of local GDP growth. As highlighted in Borusyak, Hull and Jaravel (2021), the share exogeneity assumption is also appropriate when we use tailored exposure shares in the SSIV, which is the case in this framework.

As usual, the validity condition cannot be verified directly though I run recommended falsification tests. The IV validity may not hold if local authorities with different grant shares have other characteristics that can explain trends in local GDP growth other than through local spending. While this cannot be tested directly, I run falsification tests, as recommended by Goldsmith-Pinkham et al. (2020), in Section 4.2 that partially assess the plausibility of the assumption. First, I perform a balance check by separately regressing the grant shares and local GDP growth on local-level observables. The test consists of checking whether each observable correlates significantly and simultaneously with both the shares and the dependent variable. Even though a significant coefficient at this stage in both regressions is not a problem per se given that the validity assumption is conditional on controls it could point towards an omitted variable problem. In a second test, I instrument the baseline specification with the lagged grant shares interacted with year fixed-effects as separate instruments in a many-IV 2SLS setting, i.e. instrumenting with $s_{lk,t-1}$ interacted with time fixed-effects instead of B_{lt}. This procedure is based on the fact shown by Goldsmith-Pinkham et al. (2020) that the Bartik estimator is equivalent to a GMM estimation that uses lagged local shares as instruments and a specific weight matrix whose components are called "Rotemberg weights." As such, this shares-directly 2SLS produces an unweighted estimate that should be similar to the baseline SSIV estimate under homogeneous effects. Fiscal multipliers, however, are known to vary with the business cycle implying that the test will fail. Nonetheless, it is still useful to analyze the Rotemberg weights to check whether the heterogeneity pattern makes sense.

4 Results

In this section I present evidence of how local heterogeneity affects the fiscal multiplier. First, I pin-down an average estimate of the multiplier using the baseline specification for both revenue and capital spending. I then run robustness checks for the SSIV design and show evidence to support the identification strategy. Next, I assess fiscal multiplier heterogeneity by spending category. Finally, I identify a set of local parameters that can explain the variation in the local fiscal multiplier between LADs and show direct evidence that the underlying mechanism is not variation in local MPCs.

4.1 Fiscal Multiplier

Before analyzing possible sources of heterogeneity, it is important to pin-down the average local fiscal multiplier to put the effects of heterogeneity into perspective. I proceed using the benchmark specification showed in Equation 1 where I use change in real per-capita local spending as my main regressor and local GDP per-capita growth as the dependent variable. Regarding the central government grants listed in Section 2 I only use non-earmarked grants, which consist of the majority of the central government funding, to construct the instrument shares. I also do not use grants that are linked to changes in local business taxation as those are likely not valid as instruments.[7] I then construct the shift-share IV in Equation 2 using the lagged within AEF specific grants share of local GDP.[8]

While I do have disaggregated data on the individual grants that compose the within AEF grant bin, I choose to work with a single aggregated grant bin, i.e. I sum all grants within the AEF. This is due to significant noise at the grant level. Using individual grants separately to calculate the SSIV in Equation 2 is impractical given the frequent policy changes how grants are labelled. Grants are frequently created, renamed, split, merged, and ended depending on what the central government is focusing on in a given year. Take for instance the "Early Intervention Grant" (EIG), an early education grant that was created in 2010 by bringing together several smaller grants. Its creation also included changes in how the grant was allocated and how much money the central government was willing to spend on it. In 2013 it was decided that the EIG grant would no longer be paid as a separate grant. It would instead show up under different grants such as the

[7] This excludes the Revenue Support Grant. I further exclude the Police Grant which is awarded directly to local police bodies. These are treated as a separate local entity in the local spending accounts and are excluded from my sample.

[8] In certain years, I also add temporary general grants called Local Services Support Grant and Area-Based Grant as those were created from a relabelling of previous specific grants.

Dedicated Schools Grant (DSG). Since the underlying purpose of the funding remains the same (both EIG and DSG are "within" AEF grants), I can use the yearly aggregated sum to capture movements in government funding while avoiding changes that are essentially in form. This cleans the SSIV of much of the noise generated by single grants life cycle while effectively capturing the weight of the central government on local budgets.[9]

It is also important to highlight a few differences with the benchmark case in Goldsmith-Pinkham et al. (2020). First, I am dealing with an "incomplete shares" case where the local GDP share of all central government grants is not one. As shown in Borusyak et al. (2021), this would require controlling for the total sum of shares in each locality. However, since I am aggregating grants into a single bin we have $k = 1$ which implies that the total sum of shares is already factored in. In our case, however, the threat to identification comes from the earmarked grants which were not included in the SSIV calculation. If earmarked grant awards correlate with the non-earmarked grants used in the SSIV, our estimate will be biased. To deal with this issue, I show fiscal multiplier results where I also control for the local per-capita amount of grants outside the AEF. To further strengthen our identification, I add to the control set the other LAD funding sources, i.e. council tax, non-domestic rates charged from businesses (though set-up nationally), the per-capita amount of people receiving fiscal transfers, and the stock of reserves held by the local authority.

I now proceed with the estimation of the benchmark setting. I show in Table 1 the 2SLS results using next-period GDP growth and next-period employment change as my dependent variables.[10] Columns (1)-(4) report the next-period fiscal multiplier while columns (5)-(8) report the employment fiscal multiplier. Columns (1) and (5) have no local-level controls, columns (2) and (6) add several council-level controls, columns (3) and (7) control for the one-year lagged outside AEF per-capita grant amount, and columns (4) and (8) add local controls together with the lagged outside AEF grant amount. Controlling for grants not included in the SSIV allows us to compare councils that receive the same amount of central government grants not included in the SSIV while exploiting grant heterogeneity in non-earmarked grants, effectively accounting for total reliance on central government funding. Finally, standard errors are clustered at the county level for non-metropolitan districts and at the LAD-level for the other observations in all specifications, and the heteroskedastic-robust F-statistic for the instrument, which is reported at

[9] I show estimation results using grant bins aggregated by large spending categories (e.g. education, social care) in Table A.2. Point-estimates are statistically indistinguishable from baseline ones.

[10] Figure A1 in the Appendix shows the binned scatter plots for the first-stage and the reduced form results of the next-period GDP growth specification controlling for year and council fixed-effects. It shows strong IV relevance and a positive correlation between the SSIV and local GDP growth, both of which do not seem to be driven by outliers.

the bottom of the table, is well above the usual threshold level for the weak-IV test.

Table 1: Local Service Spending Fiscal Multiplier Estimates

	GDP_{t+1}				Emp_{t+1}			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Multiplier	1.738**	1.666**	1.769**	1.693**	0.140	1.725	0.0417	1.813
	(0.791)	(0.785)	(0.806)	(0.798)	(1.434)	(1.321)	(1.471)	(1.194)
N	3,235	3,235	3,235	3,235	3,235	3,235	3,235	3,235
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Council FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls		Yes		Yes		Yes		Yes
Outside AEF Grants			Yes	Yes			Yes	Yes
Robust F-statistic	100.8	108.9	101.0	109.8	100.8	102.8	101.0	108.9

Notes: Main regressor corresponds to growth in real local authority total service expenditure per-capita. GDP_{t+1} corresponds to local GDP per-capita growth one period ahead scaled by one-year lagged GDP per-capita. Emp_{t+1} corresponds to local employment per-capita growth from $t-1$ to $t+1$. Local-level controls (one-year lagged): share of NVQ3 awards (equivalent to a high-school diploma), unemployment rate, median age, child poverty rate, average full-time wage, per-capita number of people receiving central government benefits (for Disability Living Allowance, Incapacity Benefits, Housing Benefit, Universal Credit, Personal Independence Payment, and Child Benefit) where each claimant counts by the number of individual benefits they receive, dummies for the political party controlling the local council, LAD reserves per-capita, per-capita amount of funds from non-domestic rates, and average council tax. Outside AEF Grants is the per-capita amount of all grants outside the AEF which are not included in the SSIV. Standard errors are clustered by counties for non-metropolitan districts and by individual LAD for the rest. *, **, *** denote significance at 10%, 5%, and 1% levels, respectively.

Starting with columns (1)-(4), we observe that point-estimates are larger than one and significantly different from zero. Adding the lagged earmarked grant funding as a control does not affect estimates significantly, nor does adding local-level controls and controlling for other sources of LAD funding (i.e. fiscal reserves, non-business rates, and council tax). My preferred fiscal multiplier estimate of 1.69 is close to the 1.9 median estimate in the literature on regional multipliers (Chodorow-Reich, 2019) although the literature is mainly about the multiplier of direct fiscal transfers. This is evidence that service-based fiscal multipliers can have a similar magnitude to those calculated from fiscal transfers. On a side note, although point-estimates are above 1 they are not significantly different from it. As the point of the analysis later on is to show multiplier heterogeneity, I will not focus on the average estimate.

I show results are robust to changes in the benchmark specification. I run different yet similar specifications to Equation 1 in Table A.2 in the Appendix. Results are robust to running a weighted specification weighting by the one-year lagged logarithm of LAD population (columns (1) and (2)), to using two-year lagged grant shares when constructing the SSIV, that is when using $s_{lk,t-2}$ in Equation 2(columns (3) and (4)), and to using fixed initial grant shares, i.e. $s_{lk,0}$, which follows the SSIV convention (columns (5) and (6)).[11] In the initial shares case all controls are fixed at the same time period as the shares and interacted with year fixed-effects. As initial-period shares become less relevant in later periods, there is a significant drop in first-stage relevance when controls are added in. Moreover, results remain unchanged if instead of using $(Y_{l,t+1} - Y_{lt})/Y_{l,t-1}$ as our dependent variable we use $(Y_{l,t+1} - Y_{lt})/Y_{lt}$ (columns (7) and (8)). In all specifications, point-estimates are statistically indistinguishable from benchmark ones.

As an additional step, I show results are robust to calculating the SSIV at a more disaggregated grant level. As aforementioned, I aggregate all non-earmarked central government grants that are not related to local business taxation funds when calculating the SSIV. We can, however, aggregate grants by broad spending category k (c.f. Equation 2) which requires matching individual grants to a category. I do so in columns (9) and (10) of Table A.2 in the Appendix for the following categories: education, social care, local development, housing, and healthcare (leftover grants are binned together as "other"). Point estimates are higher though they remain statistically indistinguishable from baseline ones and significantly different from zero. As expected, we observe a drop in first-stage relevance. It is also worth noticing that, differently from the baseline case, here we have to control for the one-year lagged sum of non-earmarked grants. This is because the specification deals with "incomplete shares" where individual spending category shares do not add up to a constant (Borusyak et al., 2021). As such, I add the total share as a control in columns (9) and (10).

It is important to highlight at this point what the local multiplier results mean. Since I am relying on local council variation to pin-down the local multiplier, results imply that a 1% increase in an LAD's spending *relative* to other local councils increases *relative* local GDP by 1.69%. As such, results do not take into account spillover effects where spending in one LAD might affect a neighboring local authority, nor general equilibrium effects acting, for instance, via inter-council migration and commuting patterns. One way to assess these effects is to run the specification at a different geographical level. I do so at the level of "travel-to-work areas" (TTWA) which are commuting regions in the UK.[12] I show in Table A.3 in the Appendix estimates for the fiscal multiplier at the TTWA level. Since LADs are not associated 1:1 with TTWAs, I link each local authority to the TTWA that contains the majority of its postcodes. Notwithstanding the lower number of observations and the fact that local grants are not awarded at the travel-to-work level, two facts that

[11] Typically, shares are fixed in a period before a policy in which the instrument is based on comes into effect (i.e. a pre-period). Since my sample starts in the fiscal year of 2007-08, there is no pre-period. Nonetheless, the validity assumption works with any amount of time lag.

[12] While there are 398 councils in the UK, there are only 228 travel-to-work areas.

explain the drop in instrument relevance, estimates are close to the ones calculated at the council-level. This provides evidence that results at the LAD-level are possibly relevant at larger geographical levels and are not significantly affected by commuting and migration patterns.

I further find no effect of local spending on employment. As shown in columns (5)-(8) of Table 1, the estimate for employment is not statistically significant.[13] The estimation uses Equation 1 except that now the dependent variable is the two-year change in employment (i.e. $(L_{l,t+1} - L_{l,t-1})/L_{l,t-1}$, where $L_{l,t}$ is employment per capita). As such, an increase in local spending does not seem to generate new jobs, despite local authorities being able to hire directly in the labor market.

We can also analyze the short-term multiplier effect of capital spending. Although results so far have been about public service provision, which corresponds to most of local spending, local authorities also invest in fixed assets such as schools, vehicles, and intangibles.[14] As with services, councils receive central government grants which can be used for local capital investing. We can, then, apply a similar specification to Equation 1 to estimate the fiscal multiplier of public capital spending where I instrument local government spending with an SSIV calculated using central government capital grants.

Results for capital spending are shown in Table 2. In columns (1) and (2) I report the one-period-ahead fiscal multiplier for capital spending growth calculated over two years to take into account possible adjustment costs in capital investing. As with services, the capital multiplier estimate is above one and statistically significant, implying that a 1% increase in a council's capital investing relative to other local councils increases relative local GDP by 1.71%. This estimate is close to the services one of 1.69. We can, then, ask whether service and capital spending are confounding each other's fiscal multiplier estimates as spending patterns may be correlated. I assess this point in columns (3)-(6) where I regress local GDP growth on both service and capital spending, each instrumented with their respective central government grant SSIV.[15] Although instrument relevance is weaker given the more demanding specification, results show that there is little bias from regressing each type of spending separately as estimates barely change, especially for capital spending whose fiscal multiplier is identified more precisely.[16] This

[13]To get employment multipliers, we have to multiply the table coefficients by the employment-to-GDP ratio.

[14]Fixed asset investment corresponds to around 16% of total local public expenditure in sample.

[15]Grant shares for services are two-year lagged, i.e. $s_{lk,t-2}$, to match capital shares which are two-year lagged since the change in capital spending is over two years.

[16]I report multipliers for total local spending, i.e. services and capital expenditure combined, in Table A.4 for both one-year and two-year changes in spending. Estimates are statistically significant in all specifications and indistinguishable from benchmark ones.

is reassuring from the point of view of instrument validity.

Table 2: Local Capital and Services Spending Fiscal Multiplier Estimates

	GDP_{t+1}					
	(1)	(2)	(3)	(4)	(5)	(6)
Capital Spending_{2y}	1.574***	1.706***	1.502***	1.613***	1.616***	1.673***
	(0.540)	(0.561)	(0.552)	(0.571)	(0.548)	(0.564)
Service Spending			1.091	1.313	1.168	1.345
			(1.012)	(1.051)	(1.032)	(1.066)
N	2,938	2,938	2,938	2,938	2,938	2,938
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Council FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls		Yes		Yes		Yes
Outside AEF Grants					Yes	Yes
Robust F-statistic	69.4	63.8	35.7	32.8	36.0	33.7

Notes: Main regressors correspond to growth in real local authority capital and service expenditure per-capita. SSIV for service spending uses two-year lagged grant shares to match the timing of the capital grant shares. Subscript $2y$ indicates that the change is over two years. GDP_{t+1} corresponds to local GDP per-capita growth one period ahead. Local-level controls (two-year lagged): share of NVQ3 awards (equivalent to a high-school diploma), unemployment rate, median age, child poverty rate, average full-time wage, per-capita number of people receiving central government benefits (for Disability Living Allowance, Incapacity Benefits, Housing Benefit, Universal Credit, Personal Independence Payment, and Child Benefit) where each claimant counts by the number of individual benefits they receive, dummies for the political party controlling the local council, LAD reserves per-capita, per-capita amount of funds from non-domestic rates, and average council tax. Outside AEF Grants is the per-capita amount of all grants outside the AEF which are not included in the SSIV. Standard errors are clustered by counties for non-metropolitan districts and by individual LAD for the rest. *, **, *** denote significance at 10%, 5%, and 1% levels, respectively.

Results, then, show that public spending on services and capital have, on average, multipliers whose point-estimates are above one. It is not clear, however, whether such multipliers present heterogeneity between councils and, if so, whether it is related to usual explanations involving differences in individual-level MPCs. I analyze this point further in Sections 4.3 and 5 when discussing a mechanism behind the larger-than-one multiplier and its underlying local heterogeneity.

4.2 Robustness of the SSIV Design

The main concern in a "shares-based" shift-share framework is the violation of the conditional exogeneity assumption regarding local shares. For that to happen, unobservable correlates of the lagged grant shares need to have some explanatory power over the outcome variable, i.e. local-level real GDP growth. While this assumption cannot be verified directly it is useful to understand how shares are correlated with observables and how each observable might be correlated with the outcome variable. While I control for these observables in the main specification, it could still be the case that places with different values of observables have systematically different unobservables which would violate the validity condition of the shift-share instrument.

To assess this point, I run a balance test in Table A.5 in the Appendix by regressing the local-level observables on local grant shares and local GDP growth. I also show results for the largest grant inside the AEF, i.e. the Dedicated Schools Grant (DSG). The SSIV passes the balance test if there is no simultaneous significant coefficient in columns (1) and (2), or columns (3) and (4). All variables are demeaned and normalized to have unit variance so that coefficients are more easily interpretable. We observe that there are no balance issues with the DSG share as no covariate has a significant coefficient with both the DSG share and GDP growth. However, the local council being under the control of the Liberal Democrats (LD) poses a threat to identification with respect to the aggregated grant share as the coefficients are statistically significant in both columns (3) and (4). The magnitude of the correlation is relatively high as being controlled by the LD relative to the Conservatives is associated with a decrease in the grant share by 13% of its standard deviation and a decrease in growth by 23% of its standard deviation. However, only 4.5% of all LAD-year observations have a local council controlled by the Liberal Democrats. As such, the imbalance between high-share and low-share councils regarding political control by the LD does not seem to be substantial enough to affect our multiplier results in Table 1.[17]

Since the SSIV combines council-level grant shares in different years to construct a single instrument, it is also useful to analyze the contribution of each individual grant share (i.e. $s_{lk,t-1}$ for each t) to the estimation. As shown in Goldsmith-Pinkham et al. (2020), the shift-share IV estimation is equivalent to a GMM estimation using moment conditions on the shares and a specific weight matrix. These (Rotemberg) weights, which are calculated for each year t, tell us how sensitive our baseline estimate is to misspecification (i.e. endogeneity) in a particular year and they depend on the covariance between the first-stage fitted value calculated for each year using $s_{lk,t-1}$ as an instrument and the endogenous variable.[18] As such, we can run a 2SLS estimation using each yearly grant share separately as an instrument by interacting them with year fixed-effects to calculate unweighted estimates. Specifically, let T be the total number of years in the sample. We

[17]Removing LAD-year observations where the LD have control of the council results in a multiplier of 1.66 in the specification with all controls vs. 1.69 for the benchmark.

[18]In the simplest example where the individual, yearly instruments are all orthogonal to each other, the weights are simply the ratio between the just-identified first-stage R^2 and the full SSIV first-stage R^2.

then run the following first stage:

$$\frac{G_{lt} - G_{l,t-1}}{Y_{l,t-1}} = \sum_{t \in T} \delta_{kt} s_{lk,t-1} + \xi X_{l,t-1} + \phi_l + \psi_t + \eta_{lt} \tag{4}$$

where the second stage is the one shown in Equation 1.

The fiscal multiplier estimate calculated using this many-IV 2SLS should coincide with the ones in Table 1 in a setting with homogeneous treatment effects in time. However, since we know that fiscal multipliers calculated during expansions and recessions differ, we should expect the estimates calculated instrumenting with grant shares directly to be different from our benchmark ones.[19]

I show in Table A.6 in the Appendix the Limited Information Maximum Likelihood (LIML) results instrumenting with the lagged grant shares directly in a many-IV setting. The choice for the LIML estimator is due to its better small-sample properties in settings with many instruments where some instruments are weak. As expected, the coefficients are not close to the ones in Table 1 although grant shares show sufficient instrumental relevance. Moreover, we reject the null hypothesis of the overidentification tests. To understand this failure in our context, we can calculate year-specific fiscal multipliers $\hat{\beta}_t$ by instrumenting Equation 1 with the year-specific shares. If we assume heterogeneous effects between the fiscal multipliers $\hat{\beta}_t$ calculated over different years, the failure of the overidentification tests does not point towards instrument misspecification since we expect some dispersion in the $\hat{\beta}_t$'s caused by heterogeneity.

We, then, analyze the heterogeneity in the individual $\hat{\beta}_t$ by calculating their respective Rotemberg weights. I plot the heterogeneity of $\hat{\beta}_t$ in Figure A2 in the Appendix where the size of each point is scaled by its Rotemberg weight and where I use the specification in column (8) of Table 1. The figure shows why the overidentification test failed: there is significant dispersion in the $\hat{\beta}_t$'s, particularly between 2011 and 2012 which are the two years with largest weights.

I report in Table A.7 in the Appendix the summary statistics for the Rotemberg weights along with details on the years with largest weights. The main takeaway is that the two years with the highest weights (i.e. 2011 and 2012, accounting for more than 85% of the yearly weight) were years of large reductions in central government grant funding, as seen in Panel C. In 2011 and 2012, 97% and 90% of LADs saw a reduction in their grant funding, respectively, with a cumulative aggregate decline of around 0.6% of GDP in real

[19] C.f. Nakamura and Steinsson (2014), Auerbach and Gorodnichenko (2012). The presence of heterogeneous effects when using a shift-share instrument to calculate fiscal multipliers was also noted in Brandao-Roll et al. (2024).

terms. We can then explain the heterogeneity in $\hat{\beta}_t$ between 2011 (0.95) and 2012 (4.81) which is behind the failure of the overidentification test in Table A.6. While the first year of fiscal austerity seems to have led to some increase in service efficiency, causing the multiplier estimate to be lower than the average estimate of 1.69 as local GDP did not as much as spending, the subsequent reduction in funding was linked to a large drop in local GDP as the multiplier estimate becomes larger. This yearly heterogeneity is similar to the one observed between periods of fiscal expansion and contraction,[20] although my results highlight the importance of understanding the context when fiscal changes happen as one year of contraction might not lead to the same conclusion as two years of fiscal austerity.

As such, we can attribute the overidentification test failure to the yearly heterogeneity stemming from two sequential periods of fiscal contraction. It is then natural that the overidentification tests in the many-IV 2SLS estimation failed and should not be seen as a sign of misspecification. Moreover, as seen in Figure A2 the years with large weights also have large first-stage F-statistics which is reassuring from a small-sample bias point of view. Finally, although we observe years with negative weights they are not relevant for the overall result as the combined weight of positive-weighted years corresponds to around 96% of the overall weight share as shown in Panel A of Table A.7.

4.3 Underlying Channels and Local Multiplier Heterogeneity

In this section I analyze both the channels through which local public spending increases local GDP and the underling fiscal multiplier heterogeneity between local authorities with respect to type of spending, local labor market, and demographic characteristics. The goal is to understand how the fiscal multiplier varies according to local-level aspects and to show that this local heterogeneity cannot be explained by the expected variation in marginal propensities to consume.

To assess whether we observe heterogeneity in the fiscal multiplier at the LAD-level, I use the following specification:

$$\frac{Y_{l,t+1} - Y_{lt}}{Y_{l,t-1}} = \beta \frac{G_{lt} - G_{l,t-1}}{Y_{l,t-1}} + \delta_2 \frac{G_{lt} - G_{l,t-1}}{Y_{l,t-1}} \text{ x } D_{l,t-1} + \delta_1 D_{l,t-1} + \gamma X_{l,t-1} + \phi_l + \psi_t + \epsilon_{lt} \tag{5}$$

where $D_{l,t-1}$ is the council-level characteristic of interest at time $t-1$. As in Section 4, I instrument local spending growth with the shift-share instrument based on the lagged grant share of local GDP, both by itself and interacted with $D_{l,t-1}$.

[20] A point made in Riera-Crichton, Vegh and Vuletin (2015), Jordà and Taylor (2016), and Pragidis, Tsintzos and Plakandaras (2018).

I show results using the preferred benchmark specification in Table 3. I analyze the fiscal multiplier heterogeneity using the following local variables, all of which have been demeaned and normalized to have unit variance: economic inactivity per-capita,[21] share of those who are inactive who want to work, average anxiety level,[22] low-skill labor per-capita, child-poverty rate, per-capita number of people receiving benefits, average wage of full-time workers, and wage inequality measured as the wage ratio between the 60^{th} and the 20^{th} percentiles. We assess this table in two parts. First, columns (1)-(4) show considerable heterogeneity in the fiscal multiplier with respect to local variables. In columns (1) and (4) the coefficient of the interaction is negative and statistically significant. This suggests that higher economic inactivity per-capita and low-skill labor share decrease the service and capital spending fiscal multipliers, respectively. Columns (2) and (3) on the other hand report the opposite: the coefficient on the interaction is positive. This implies that having more people in inactivity who want to work and higher anxiety levels increase the local fiscal multiplier. All specifications include time and council fixed-effects, council-level controls (including the interaction term), and I am also controlling for the local authority spending share of different spending categories to show that results are not driven by heterogeneity in spending categories.[23] First-stage robust F-statistics are all above the usual threshold for weak instruments.

Figure 2 summarizes the effect of the local variables on the fiscal multiplier. The arrows show how the baseline multiplier (around 1.7 for both service and capital spending) changes given a one standard deviation addition to the mean of each local characteristic in Table 3, i.e. each arrow starts at the baseline multiplier estimate $\hat{\beta}_{base}$ and ends at $\hat{\beta}_{base} + \delta_2$ all else constant, where δ_2 is the interaction coefficient in Equation 5 and Table 3. For example, as we increase by one standard deviation the per-capita inactivity level from its mean value the estimated multiplier decreases from 1.7 to 1.1, all else being equal, which corresponds to a 35% decrease in the multiplier. This is evidence that there is significant fiscal multiplier heterogeneity as a function of local-level parameters, as those are able to shift the fiscal multiplier around a range of values from 0.6 to 3.0.

We now analyze the second part of Table 3. As has been shown in the literature of fiscal multipliers, we would expect variation in estimates driven by MPC variation at the

[21]Inactivity is defined as people not in employment who have not been seeking work in the previous 4 weeks and/or are unable to start work within the next 2 weeks.

[22]Anxiety levels are measured via well-being a survey conducted by the ONS and vary on a scale from 0 to 10.

[23]Spending categories shares included in the set of controls are transportation, education, social-care, housing, cultural, planning, central, and environmental.

Table 3: Local-Level Fiscal Multiplier Heterogeneity

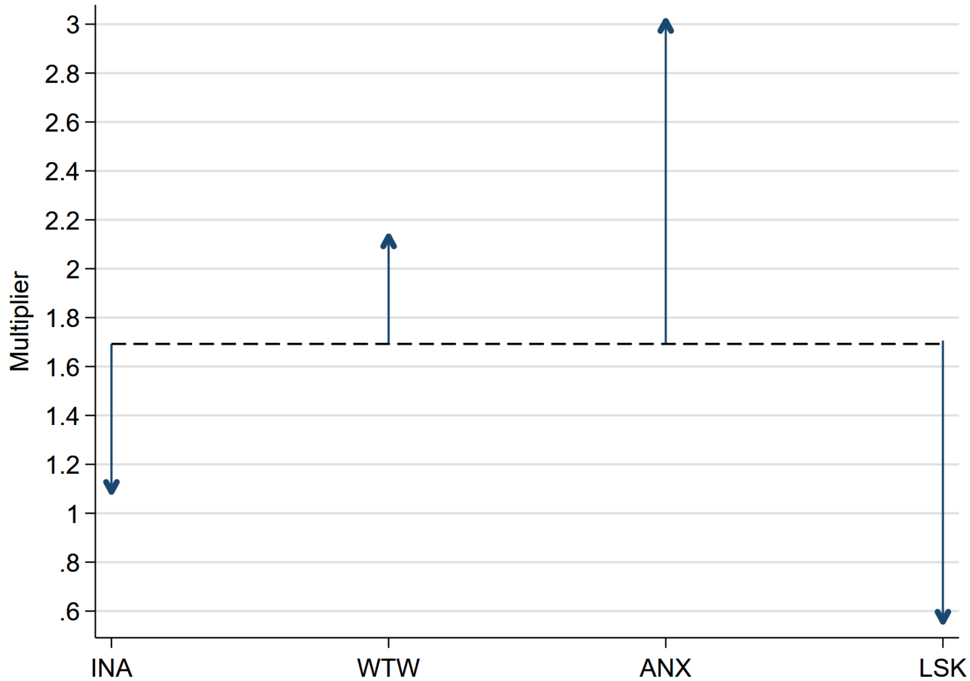
	GDP$_{t+1}$							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Service Spending	2.324**	1.606**	1.795		1.754*	1.460	1.521*	1.536
	(0.902)	(0.812)	(1.824)		(0.983)	(0.958)	(0.807)	(1.011)
Service Spending × D	-0.605*	0.439*	1.320**		-0.052	0.104	-0.211	-0.118
	(0.314)	(0.227)	(0.588)		(0.253)	(0.229)	(0.264)	(0.522)
Capital Spending				1.644***				
				(0.530)				
Capital Spending × D				-1.136*				
				(0.625)				
Interaction	INA	WTW	ANX	LSK	CPV	BEN	INE	WAG
N	3,228	3,228	2,369	2,702	3,228	3,228	3,228	3,228
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Council FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Spending Category	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Outside AEF Grants	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Robust F-test	46.4	49.0	12.6	14.2	40.5	37.9	44.3	30.2

Notes: Interaction variables: INA - inactivity per-capita, WTW - 3-year rolling average of the share of those in inactivity who want to work, ANX - average anxiety level, LSK - low-skill labor per-capita, defined as those with a fail GCSE grade mark (or equivalent) or lower, CPV - child-poverty rate, BEN - per-capita number of people receiving central government benefits, INE - wage inequality measured as the ratio of the 60th percentile over the 20th percentile, WAG - real average full-time wage. Main regressors correspond to growth in real local authority service and capital expenditures per-capita. GDP$_{t+1}$ corresponds to local GDP per-capita growth one period ahead. Local-level controls (one-year lagged): D, share of NVQ3 awards (equivalent to a high-school diploma), unemployment rate, median age, child poverty rate, average full-time wage, per-capita number of people receiving central government benefits (for Disability Living Allowance, Incapacity Benefits, Housing Benefit, Universal Credit, Personal Independence Payment, and Child Benefit) where each claimant counts by the number of individual benefits they receive, dummies for the political party controlling the local council, LAD reserves per-capita, per-capita amount of funds from non-domestic rates, average council tax, and 60-to-20th wage inequality. Outside AEF Grants is the per-capita amount of all grants outside the AEF which are not included in the SSIV. Spending Category controls for the one-year lagged share of spending in transportation, education, social-care, housing, cultural, planning, central, and environmental. Standard errors are clustered by counties for non-metropolitan districts and by individual LAD for the rest. *, **, *** denote significance at 10%, 5%, and 1% levels, respectively.

local level if fiscal spending here were about transfers.[24] I argue through three points that the heterogeneity observed in Table 3 cannot be entirely explained by differences in local MPCs. First, as aforementioned I do not include fiscal transfers as part of local public spending. Although public services and capital can still increase GDP via MPCs by boosting disposable incomes as LADs provide free services that may substitute those offered by

[24]C.f. Kaplan and Violante (2018) for a review of models that can generate significant MPC heterogeneity. On the literature of fiscal multiplier heterogeneity from MPCs, c.f. Anderson, Inoue and Rossi (2016), Brinca, Holter, Krusell and Malafry (2016), Carroll, Slacalek, Tokuoka and White (2017), to cite just a few.

Figure 2: *Expected Change in the Fiscal Multiplier for Different Local Characteristics*



Notes: Expected change is calculated as the baseline fiscal multiplier from Column (8) of Table 1 plus the respective interaction coefficient in Table 3. Interaction variables: INA - inactivity per-capita, WTW - 3-year rolling average of the share of those in inactivity who want to work, ANX - average anxiety level, LSK - low-skill labor per-capita, defined as those with a fail GCSE grade mark (or equivalent) or lower.

private firms that charge for them, this can only happen indirectly here as funds have to be spent in providing an actual service.[25] Second, I use the specification in Equation 5 to assess the effect on the multiplier from variables that are more commonly associated with variation in MPCs which I show in columns (5)-(8). These variables are: child-poverty rate, per-capita number of people receiving benefits, 60^{th}-to-20^{th} wage inequality, and average wage of full-time workers. Interestingly, none of the results shows evidence of the MPC channel in explaining multiplier heterogeneity as all interaction coefficients are not statistically significant even though we would expect MPCs to correlate positively with the first three variables and negatively with average wages (controlling for inequality). As poor households usually have high MPCs, we would expect the interaction coefficients in columns (5)-(7) to be positive and significant, and negative and significant in column (8) if results were being driven by differences in marginal propensities to consume. More-

[25]We can also consider the more direct MPC channel from public service wages as local authorities may hire more workers with their funds. However, not only the employment fiscal multiplier in Table 1 is not statistically significant but it is also unclear how this hiring would correlate with the local variables in Table 3 so as to explain the multiplier heterogeneity via public service employees' MPCs.

over, I already control in Table 3 for observables associated with MPC heterogeneity such as child poverty, unemployment, and inequality. While this evidence does not rule out completely that fiscal multiplier heterogeneity is being driven by differences in MPCs, it does show that my results are not being majorly driven by MPC heterogeneity.

I make a third argument against the MPC channel by providing direct evidence of alternative fiscal multiplier heterogeneity channels. I show in Table 4 two important sets of results. First, I show evidence of local heterogeneity in how fiscal spending affects labor productivity and employment. Columns (1)-(5) show evidence that the fiscal multiplier heterogeneity in Table 3 can be explained by how local variables change the relationship between local spending and labor market outcomes. While column (1) shows that higher inactivity lowers the hourly productivity boost from local service spending, columns (2) and (3) show the opposite for the share of those in inactivity who want to work and the average anxiety level. As for capital spending, columns (4) and (5) show evidence that more low-skill labor dampens the increase in per-job productivity and can lead to a negative employment multiplier. Second, Table 4 shows evidence using the benchmark specification that local public spending reduces the impact of disease on the population, child poverty, and inactivity for those who want to work.

Results, then, complement those in Table 3 as they show evidence of what is driving the heterogeneity in the fiscal multiplier. As both labor productivity and employment levels are affected differently by local spending depending on local characteristics, results show evidence that local services and capital have a direct effect on labor market parameters. Such results are hard to explain via the MPC channel.[26] Similarly, as fiscal spending lowers the incidence of disease risk factors, poverty, and economic inactivity through health and social care, we can associate the improvement in social conditions with better labor market outcomes.

Finally, I complement the previous result on labor market outcomes and improvements in local social conditions with evidence of heterogeneity by spending category. As local authorities provide services for several spending categories, we can assess whether each category affects local GDP differently. However, as I only have an instrument for total service expenditure I cannot control for simultaneous changes in spending for each category which raises the issue of potential bias in estimates as LADs can shift resources from one category to another. Instead of using Equation 1, I use the change in the category-specific share of total spending, i.e. $(G_{clt}/G_{lt}) - (G_{cl,t-1}/G_{l,t-1})$ where G_{clt} is local public spend-

[26] Given the lack of data on capital utilization, it is not possible to disentangle the observed increase in labor productivity and an increase in the capital utilization rate. However, it is hard to see how a higher capital utilization rate supported by higher MPCs would explain the heterogeneity observed in Table 3, i.e. how capital utilization correlates with the local observables.

Table 4: Local-Level Fiscal Multiplier Heterogeneity

	Hourly Productivity			Per-Job Productivity	Emp	DALY	Child Poverty	Inactivity But Wants Job
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Service Spending	2.070**	1.133	2.801			-1.004***	-5.519***	-19.56**
	(0.995)	(0.890)	(1.971)			(0.345)	(1.837)	(8.706)
Service Spending $\times$ D	-0.800**	0.542*	0.997*					
	(0.331)	(0.307)	(0.570)					
Capital Spending				2.741***	-0.886			
				(0.804)	(1.125)			
Capital Spending $\times$ D				-1.719*	-3.065*			
				(1.022)	(1.652)			
Interaction	INA	WTW	ANX	LSK	LSK			
N	3,228	3,228	2,369	2,702	2,702	2,938	3,235	2,938
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Council FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Spending Category	Yes	Yes	Yes	Yes	Yes			
Outside AEF Grants	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Robust F-test	46.4	49.0	12.6	12.7	12.7	106.5	108.4	111.7

Notes: Interaction variables: INA - inactivity per-capita, WTW - 3-year rolling average of the share of those in inactivity who want to work, ANX - average anxiety level, LSK - low-skill labor per-capita. Main regressors correspond to growth in real local authority service and capital expenditures per-capita. Dependent variables in columns (1)-(3) are one-year-ahead growth rates, while all others are calculated as the change from $t-1$ to $t+1$. Per-job and hourly productivities are the ratio between deflated local GDP and total number of local jobs and total number of hours worked, respectively. Productivity growth variables are smoothed with a 3-year moving average. Local-level controls (one-year lagged): D, share of NVQ3 awards (equivalent to a high-school diploma), unemployment rate, median age, child poverty rate, average full-time wage, per-capita number of people receiving central government benefits (for Disability Living Allowance, Incapacity Benefits, Housing Benefit, Universal Credit, Personal Independence Payment, and Child Benefit) where each claimant counts by the number of individual benefits they receive, dummies for the political party controlling the local council, LAD reserves per-capita, per-capita amount of funds from non-domestic rates, average council tax, and 60-to-20th wage inequality. Outside AEF Grants is the per-capita amount of all grants outside the AEF which are not included in the SSIV. Spending Category controls for the one-year lagged share of spending in transportation, education, social-care, housing, cultural, planning, central, and environmental. Standard errors are clustered by counties for non-metropolitan districts and by individual LAD for the rest. *, **, *** denote significance at 10%, 5%, and 1% levels, respectively.

ing in category c, as my main regressor. The resulting estimate can be interpreted as the increase in local GDP growth (in 100x percentage points) if the category share of spending increases by 1. While this potential increase in the spending share is unrealistic as it would imply a level of spending that is above total actual expenditure, estimates are informative of how spending categories compare relative to one another. I show results in Table A.8 in the Appendix for the categories where the first-stage robust F-statistic was higher than

10 or close to it. We can observe that increasing social-care and planning spending shares has a positive effect on local growth, whereas increasing the education spending share has a negative effect on GDP. Although estimates for the social-care and planning categories in columns (2) and (3) are statistically indistinguishable from each other, both are higher than the education coefficient. Along with the previous evidence on local outcomes and heterogeneity, as well as the fact that social care is the second largest spending category as seen in Figure A3 in the Appendix, this heterogeneity in how different spending categories affect GDP growth points towards a fiscal multiplier mechanism where social-care services play a major role. As a side note, the negative coefficient for education spending can possibly be explained by the fact that most of the return from education takes many years to realize and is likely more reliant on inter-council migration patterns. Nonetheless, from a short-term point of view social-care spending seems to be the most relevant in raising local GDP.

These results on fiscal multiplier heterogeneity make the case for moving the local fiscal multiplier discussion away from a debate around a single value. Heterogeneity in labor market, demographic parameters, and spending categories is able to explain significant variation in estimated multipliers. Moreover, MPC heterogeneity seems unable to explain our results. If local fiscal spending can increase labor productivity, reduce economic inactivity, and improve well-being outcomes in health and poverty, the corollary is that local public spending can be thought of as being productive, and public sector productivity varies along local characteristics. I discuss a possible mechanism behind the observed heterogeneity in the fiscal multiplier in Section 5.

5 Heterogeneous Labor Model

To analyze the channel through which fiscal policy produces heterogeneous effects at the local level due to local demographic and labor market characteristics I consider a simple model of labor heterogeneity and fiscal policy. As shown in Section 4.3, any mechanism trying to explain the fiscal multiplier heterogeneity must account for the role of social-care spending and local socio-economic conditions. Here, I propose that workers are subject to a low mental bandwidth shock which effectively lowers their productivity until a high bandwidth shock arrives. This low-bandwidth shock represents different situations where the agent's cognitive bandwidth becomes scarce, e.g. poverty, sickness, and/or having to take care of a relative. Once hit by a negative shock, worker productivity drops. It then only recovers through a high bandwidth shock that is a function of government spending and worker heterogeneity regarding how hard it is to bring them back to their normal cognitive state. Given model results, I show how a social planner would opt to spend differently depending on local conditions and how this fiscal allocation compares with local public spending in the UK.

We start the set-up with two types of workers: high and low-skilled. We normalize total labor to one and assume there is an equal split between the two types on the aggregate. Workers are distributed between regions j and there is a single firm in each region that produces good c_{jt} at time t. Labor is inelastically supplied and we consider the symmetric case where there is the same amount of labor supply in each region which is entirely hired by the local firm though the shares of high and low-skilled labor vary between regions. Agent i has the following utility function:

$$
\begin{aligned}
U_i &= \sum_{t=0}^{\infty} \beta^t ln(C_{it}) \\
ln(C_{it}) &= \int_0^1 ln(c_{ijt}) dj
\end{aligned}
\tag{6}
$$

where β is the discount factor. We normalize the price of the consumption good to 1. Firm j has the following production function:

$$
\begin{aligned}
Y_{jt} &= (\gamma_{jt} L_{jt})^{\alpha} \\
\gamma_{jt} &= \frac{1}{L_{jt}} \sum_i \gamma_{ijt}
\end{aligned}
\tag{7}
$$

where γ_{jt} is the average labor productivity of workers (whose individual productivity is γ_{ijt}) hired by firm j, L_{jt} is labor, and $\alpha \in (0,1)$ is a constant. Workers in each locality j are exposed to a low mental bandwidth shock which arrives at a Poisson rate $\lambda_{jt,lb}$. Once in the low cognitive state, a worker may be hit by a high bandwidth shock at a Poisson rate $\lambda_{jt,hb}$ which brings them back to their normal state. As such, average productivity γ_{jt} changes depending on how many workers are at their low bandwidth state at any given time. Let $\gamma_{ijt} \in [\gamma_{hs,hb}, \gamma_{hs,lb}, \gamma_{ls,hb}, \gamma_{ls,lb}]$ where subscripts hb and lb mean high and low bandwidth, respectively, and hs and ls mean high and low skill, respectively. We assume $\gamma_{k,hb} \geq \gamma_{k,lb}$ for $k = hs, ls$ and $\gamma_{hs,k'} \geq \gamma_{ls,k'}$ for $k' = hb, lb$. Hence, workers switch between a state of low and high cognitive bandwidth, and these shocks affect labor productivity. A firm's average productivity will then depend not only on the share of high and low skill labor in their region but also on the incidence of shocks. We assume that firms know when a worker is in their high or low bandwidth states so that it can change wages accordingly.

As for the local government, it funds itself with a lump-sum tax $T_{ag,jt}$ on households and uses its revenues $G_{ag,jt}$ (where $G_{ag,jt} = T_{ag,jt}$) to invest in social and health care.

Hence:

$$\lambda_{jt,hb} = f(G_{ag,jt}) \ , \ f' > 0 \ , \ f'' < 0 \tag{8}$$

Next, we make an important distinction regarding how workers are affected by the low-bandwidth shock. We assume a share of workers is of "high-risk" type, i.e. when hit by a low-bandwidth shock they require more government spending, relative to the non-high-risk type, to be brought back to their normal cognitive state. The idea is to capture the difference between relatively easily revertible shocks (i.e. malnutrition) and more life-altering ones (i.e. becoming a carer for a partner with a long-term condition).[27] For high-risk individuals, the high-bandwidth shock arrives at a rate of $\theta f(G_{ag,jt})$, where $\theta \in (0,1)$. Moreover, notice that while $\lambda_{jt,hb}$ is determined by government spending, $\lambda_{js,lb}$ is exogenous.

In order not to mechanically over-tax low-skilled households relative to high-skilled ones and to take into account that high-earning agents have a larger tax burden, we consider that high-skilled households pay a larger share of taxes which is proportional to how much they earn relative to low-skilled households. As such, given a high-skill share of φ_j in local area j, then:

$$T_{ag,jt} = \varphi_j T_{jt} \frac{w_{hs,hb}}{w_{ls,hb}} + (1 - \varphi_j) T_{jt} \tag{9}$$

where $w_{hs,hb}$ and $w_{ls,hb}$ are the wages of high and low-skilled workers, respectively, at their high-bandwidth state. Given our assumption that firms adjust wages after the arrival of shocks the variation in wages comes from both skills and cognitive states, i.e. $w_{jt} \in [w_{hs,hb}, w_{hs,lb}, w_{ls,hb}, w_{ls,lb}]$. Finally, agents have the following budget constraint in expectation:

$$C_{it} = \begin{cases} E_t[w_{jt} - T_{jt} \frac{w_{hs,hb}}{w_{ls,hb}}], \ if \ high - skill \\ E_t[w_{jt} - T_{jt}], \ if \ low - skill \end{cases} \tag{10}$$

We can, then, write the household problem. Since variables do not have time-dependency, we can solve the problem statically (I remove subscripts where their absence does not hinder interpretation):

$$\max_{\{C_k\}_{hb,lb}} E(U) = \max_{\{C_k\}_{hb,lb}} \begin{cases} \frac{f(G)}{f(G)+\lambda_{js,lb}} ln(C_{hb}) + \frac{\lambda_{js,lb}}{f(G)+\lambda_{js,lb}} ln(C_{lb}), \ if \ not \ high - risk \\ \frac{\theta f(G)}{\theta f(G)+\lambda_{js,lb}} ln(C_{hb}) + \frac{\lambda_{js,lb}}{\theta f(G)+\lambda_{js,lb}} ln(C_{lb}), \ if \ high - risk \end{cases} \tag{11}$$

[27] Given inelastic labor supply, I do not allow workers to leave the labor force altogether when hit by a low-bandwidth shock. While that might be more realistic and explain heterogeneity with respect to the employment multiplier, it does not change the main results.

Equation 11 implies that each agent chooses consumption to maximize expected utility which depends on the arrival rate of both the high and the low bandwidth shocks, and whether they are high-risk individuals or not.

As for firms, they maximize per-period profits:

$$\max_{\{L_{ijt}\}_i} (\gamma_{jt} L_{jt})^{\alpha} - \sum_i L_{ijt} w_{ijt} \tag{12}$$

which implies that labor is paid at marginal productivity, i.e. $w_{ijt} = \alpha \gamma_{ijt} (\gamma_{ijt} L_{ijt})^{\alpha - 1}$.

Finally, we consider the problem of the local social planner who chooses G_{jt} to maximize aggregate welfare:

$$G_{SP} = \arg\max_{G_{jt}} ln(G_{ag,jt}) + \sum_i E(U_i) \tag{13}$$

where I make the important assumption that, along with being productive, government spending happens through the wages of LAD employees. I assume public servants are included in aggregate welfare though they are not subject to low-bandwidth shocks, for simplicity.

We can then solve Equations 10, 11, 12, and 13. To do so, I match model parameters and moments to values in the UK data. First, I define $\lambda_{jt,hb} = BG_{jt}^{\delta}$, where $\delta \in (0, 1)$ and B is a constant. Then, I calibrate the productivity parameters by matching the average wage rate for high-skill and low-skill labor. Since I do not observe individual workers in the data, I define the high-skill (low-skill) wage rate as the average wage in councils where the share of workers at the NVQ4 education level (roughly equivalent to university degree holders) is in the top (bottom) quartile of the share distribution. I then choose $\alpha = 0.8$ and $\delta = 0.8$.

This leaves us with two parameters to estimate: $\{B, \theta\}$. I proceed with a GMM estimation using the following three moments: the average fiscal multiplier estimated with the preferred specification in Table 1 (column 4), the average real local GDP per-capita, and the ratio between the average GDP of councils above and below the median value of economic inactivity per-capita of people who do not want to work. While the latter moment will help us pin-down θ, the first two are directly influenced by B. The empirical low-cognitive shock incidence is calculated using the average of the standardized (i.e. demeaned and with unit variance) local DALY, unemployment rate, and child-poverty rate.[28] I then set the minimum value of the shock arrival rate at zero and translate all values accordingly. As for the share of high-risk people, I use the per-capita amount of people in inactivity who do not want to work.

We can then proceed with the estimation by taking into account a few important details. Since the fiscal multiplier estimate in Section 4 represents the relative effect, between councils, of an additional pound spent by the local government, I calculate the model-based multiplier as the increase in consumption from a one pound increase in public spending without an equivalent increase in local taxation. We revert this procedure when we solve for the optimal fiscal policy from the central government's point of view. Finally, I consider that the low-bandwidth shock leads to a drop in average worker productivity of 20%.[29]

I show in Table 5 the parameter estimates as well as the moment fit. Overall, the fit is good. We can also check whether model-estimated multipliers show the same heterogeneity as the one observed empirically in Table 3 by regressing these multipliers on the low-bandwidth rate $\lambda_{jt,lb}$, the high-skill share, and one minus the high-risk share (so as to match Table 3). I do so in Table 6 which shows that model results match the empirical heterogeneity: while having a higher share of high-skill workers and of those in inactivity who want a job increases the fiscal multiplier, having a higher incidence of the low-bandwidth shock lowers the multiplier. Results can be explained by higher returns to public spending when resources are used to revert the negative shock to more productive workers. Similarly, having a higher share of workers who are not high-risk means a higher "bang for the government's buck."[30] As for the low-bandwidth shock, a higher $\lambda_{jt,lb}$ reduces the period of time a worker can expect to stay healthy, lowering the multiplier.

This model, hence, is able to rationalize the local heterogeneity in the fiscal multiplier shown in Section 4.3. It also highlights the role of fiscal policy in targeting both health and social care, represented here by the low bandwidth shock $\lambda_{jt,lb}$ and the share of high-risk

[28]Since data on anxiety levels only start in 2011 I do not use the estimated multiplier heterogeneity due to anxiety when calculating the expected local multiplier. Notice as well that the sample size for the capital spending multiplier estimation is smaller due to it being over two-year growth rates.

[29]This accounts for any form of psychological toll that reduces one's cognitive bandwidth, c.f. Schilbach et al. (2016) and Kaur et al. (2021) on poverty-induced stress, and Schultz and Edington (2007) for a summary on health. Although estimates for individual maladies are below 20%, the low-bandwidth shock captures the combined effect of cognitive tolls, including ones leading to absenteeism which are harder to assess in experiments.

[30]We can also interpret the high-risk share as the amount of public funds that government has to spend on welfare aspects that do not show up in the usual utility function, such as retiree healthcare, which are in the government's mandate. To be sure, the model does not take into account all aspects important for welfare.

Table 5: Model Estimation and Moment Fit

Parameter	Value	
$\gamma_{hs,hb}$	722110	
$\gamma_{ls,hb}$	507480	
B	0.003	
θ	0.52	
Moments	**Data**	**Model**
Avg. hourly wage, high-skill	20.22	20.22
Avg. hourly wage, low-skill	15.25	15.25
Avg. fiscal multiplier	1.69	1.67
Avg. real local GDP per-capita ('000)	28.3	28.8
High-to-low inactivity GDP ratio	0.82	0.97

Table 6: Model-Estimated Fiscal Multiplier Heterogeneity

	Multiplier
	(1)
$High - Skill\ Share$	0.242***
	(0.042)
$\lambda_{jt,lb}$	-0.060***
	(0.018)
$Want\ To\ Work$	0.191***
	(0.049)
N	2,410
Time FE	Yes
Council FE	Yes
Controls	Yes
Outside AEF Grants	Yes

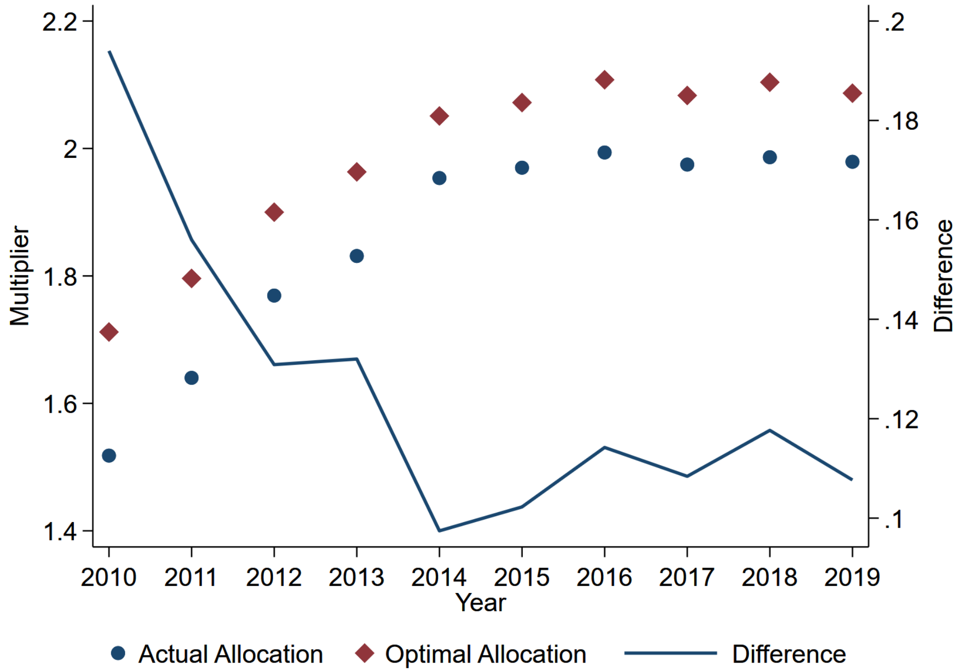
Notes: Local-level controls: share of NVQ3 awards (equivalent to a high-school diploma), unemployment rate, median age, child poverty rate, average full-time wage, per-capita number of people receiving central government benefits (for Disability Living Allowance, Incapacity Benefits, Housing Benefit, Universal Credit, Personal Independence Payment, and Child Benefit) where each claimant counts by the number of individual benefits they receive, dummies for the political party controlling the local council, LAD reserves per-capita, per-capita amount of funds from non-domestic rates, and average council tax. Outside AEF Grants is the per-capita amount of all grants outside the AEF which are not included in the SSIV. Standard errors are clustered by counties for non-metropolitan districts and by individual LAD for the rest. *, **, *** denote significance at 10%, 5%, and 1% levels, respectively.

individuals. As workers are affected by the mental (and at times physical) toll of poor health and social problems such as poverty, unexpected carer duties, and food insecurity, they become less productive. Government, then, has a role to play in choosing fiscal spending so as to provide social care.

We can finally analyze the social planner's optimal fiscal policy and compare it with actual local government grant allocation in the UK. Our planner takes the point of view of the central government who collects funds through taxation and distributes grants to local councils. Note, however, that the planner's problem described in Equation 13 corresponds to the local government's perspective. Taking now the point of view of the central government allows us to assess whether local characteristics are being taken into account in deciding local fiscal policy at the national level. Particularly, we distinguish two complementary levels of analysis: a relative one, where within a cross-section of LADs some local authorities should get more funds relative to others from a point of view of the relative fiscal multiplier between them, and an absolute one, which corresponds to optimal local fiscal policy as calculated in the model. We start with the former by calculating the average expected multiplier for each council-year pair using results from Table 3 given local inactivity and low-skill share. I show results for the distribution of average multipliers pre and post-2014 in Figure A4 in the Appendix for England. Two points are worth noticing. First, there has been an overall increase in the multiplier over time as the average jumps from 1.69 pre-2014 to 1.98 post-2014 which, from the social planner's point of view, would imply higher public spending. Second, there is substantial cross-LAD heterogeneity with an interquartile range of 0.58 pre-2014 (0.56 post-2014). This heterogeneity points towards gains from optimally rearranging the central government grant allocation even if the total amount being awarded does not change.

We start by analyzing possible gains from a better allocation of fiscal support. The natural premise behind an optimal allocation of central government grants to LADs is that councils with a higher relative fiscal multiplier should receive a fiscal boost. We assume, then, that the national government can reallocate grant funds between local authorities although it cannot change the total amount spent. We do so for each year separately, for service spending only, and for the LAD-year pairs for which we have an estimate of the local multiplier. Naturally, the best unrestricted allocation is one that gives all funding to the LAD with the highest multiplier. I adopt a more realistic approach which assumes that the central government has to allocate grants to councils where the estimated fiscal multiplier is above 1 (a "spending that pays for itself" approach). I then redistribute the total amount spent on grants proportionally to the estimated fiscal multiplier and plot the yearly actual and optimal average multipliers in Figure 3, along with the difference between both. As mentioned before, we can see that both actual and optimal multipliers increase over time. There has also been an increase in allocative efficiency of central government grants as the difference between optimal and real multipliers drops from 0.19 in 2010 (12.8% increase in the actual multiplier) to around 0.11 in 2019 (5.4% increase). However, the loss in local GDP due to this *fiscal misallocation* between LADs is still significant

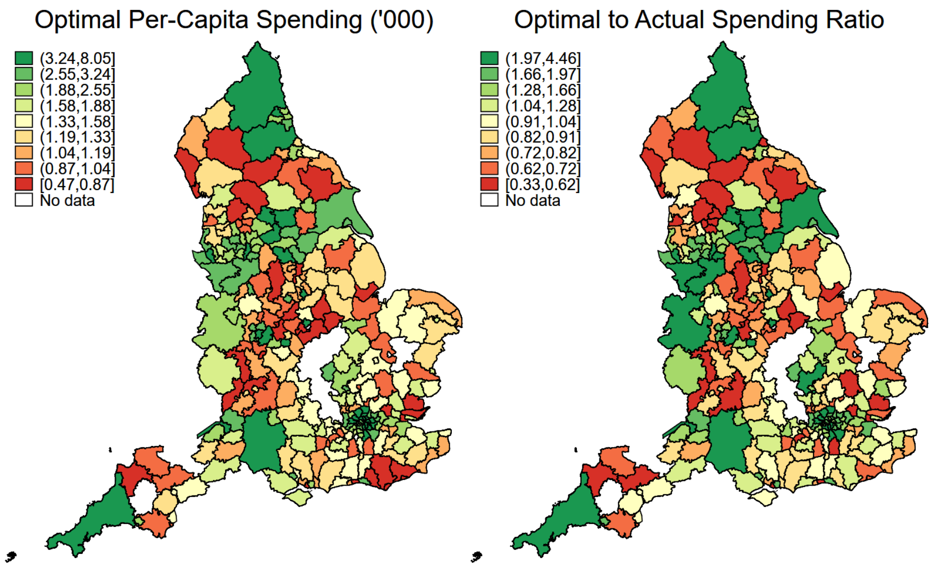
Figure 3: *Actual and Optimal Average Multipliers*



and can be measured both in terms of central government grants, which are within the purview of the national government, or total local spending, assuming the central government could directly control local budgets. Had the fiscal misallocation been corrected since 2010 for grants it would have generated an extra 57.9 billion pounds in real terms from the total grants, enough to revert the real cumulative reduction in total grant awards to local authorities since the austerity program started in 2010 (around 18 billion pounds) and double the 2019-20 total grant funding in real terms (around 39.9 billion pounds). In a more optimistic scenario where the central government could allocate the total amount spent by local budgets instead of just grants, the cumulative gains since 2010 total around 156 billion pounds in real terms, or 19.2% of the central government budget in 2019 in real terms.

We now assess fiscal spending through the local planner's solution. Although grant fiscal misallocation dropped over time, the increase in multipliers for most LADs implies that a benevolent social planner would choose to increase local spending. We can, then, solve Equation 13 using the estimated model parameters and compare the optimal spending G_{SP} with actual grant and total local spending. Importantly, we are now taking into account that any extra pound spent needs to be balanced via taxation. I show results averaged in time for each LAD in Figure 4 for England where I show both the

Figure 4: *Optimal Spending and Optimal to Actual Spending Ratio*

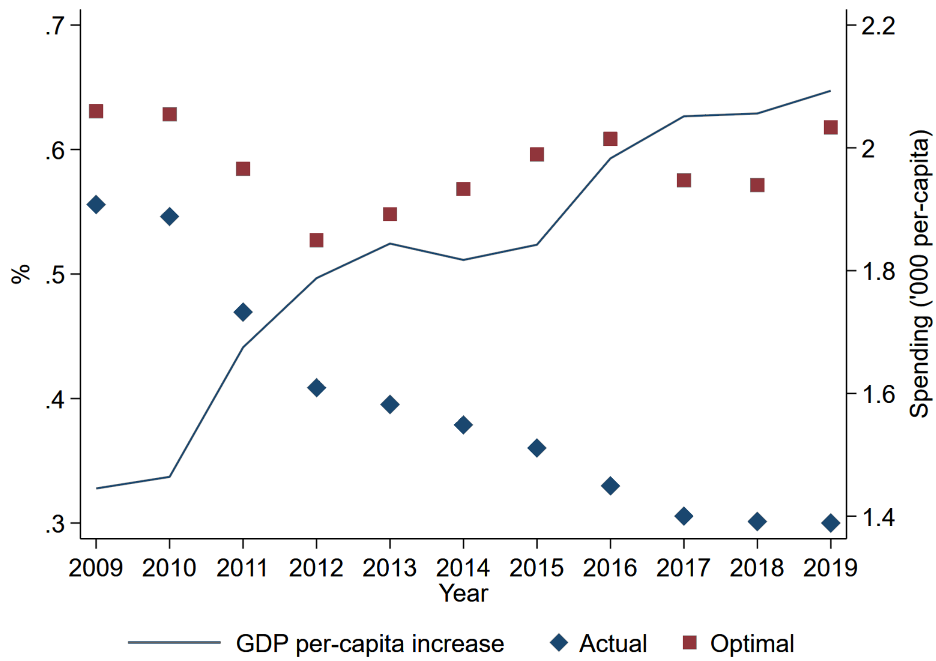


planner's solution and the ratio between G_{SP} and actual spending.[31] There are two main takeaways from results. First, there is considerable heterogeneity between councils as the interquartile range of the optimal to actual spending ratio is 0.84. This reflects our previous results on multiplier heterogeneity pointing at gains from better allocating grants and local spending. From a policy perspective, there is a significant gain from better allocating local grants as they have a low correlation (0.18) with the local planner's solution as shown visually in Figure A6 in the Appendix. Second, the social planner would prefer, on average, to increase budgets by 28% (median: 8.8%) since the average multiplier is above one.

Finally, we can gauge the overall impact on GDP from optimal local spending. Relative to the analysis of the fiscal misallocation which measured the effect of an optimal allocation keeping total spending constant and based on relative fiscal multipliers, we now assume government can determine local budgets, collects local taxes, and that fiscal spending acts through the high bandwidth shock. I show in Figure 5 the effect on the UK's yearly GDP from adopting the planner's optimal fiscal policy along with actual and optimal total spending. We observe that the gains from optimal fiscal policy have increased over time to a potential increase in GDP per-capita of around 0.65 percentage points in 2019, more than doubling the 1.2% per-capita GDP growth of that year. This

[31] A close-up of the London region is available in Figure A5 in the Appendix.

Figure 5: *Actual and Optimal Total Spending, and GDP Increase from Optimal Spending*



is due to the increase in the average local multiplier coupled with the reduction in local spending, increasing the gap between the planner's and actual policies even though the fiscal misallocation improved until 2014 as shown in Figure 3.

Results, then, imply that local fiscal policy should be seen through the lens of local heterogeneity and its causes. As the data show and the model rationalizes, labor market and demographic characteristics are important in driving the value of the fiscal multiplier as government action, particularly through social care, can boost worker productivity. Although in reality matching the planner's optimal spending might seem far-fetched given budgetary concerns, I show that there is scope for gains even in keeping total spending constant as long as an optimal allocation of central government grants reduces fiscal misallocation between local authorities. Importantly, results on LAD heterogeneity show that fiscal policy should not be reduced to a search for a single fiscal multiplier.

6 Conclusion

I exploit local variation in the reliance of local councils on central government grants in the UK to estimate the local fiscal multiplier and to understand the role of local heterogeneity in its magnitude. Assuming that the one-year lagged LAD-level grant share of local GDP is exogenous to GDP growth, changes in the aggregate disbursement of grants affect councils differently and these shares can be used in an SSIV to pin-down the fiscal multiplier. I estimate an average service multiplier of 1.69 and a capital one of 1.71, both in line with other estimates in the literature on regional multipliers. I show results are robust to running a weighted regression, to changes in the SSIV, and to running the specification at the TTWA level. I also provide evidence to support the shift-share instrument validity assumption via a balance test and an analysis of heterogeneous effects which shows estimate heterogeneity due to two subsequent years of fiscal austerity.

I then proceed to analyze the dependence of the fiscal multiplier on demographic and labor market characteristics. Councils spending similar amounts but with different local characteristics show different GDP responses to local government spending. While a higher share of economic inactivity and low-skill workers reduce the fiscal multiplier, having more people in inactivity who want a job and higher anxiety levels increase the multiplier. I argue through three points that this heterogeneity is not due to differences in local marginal propensities to consume. First, virtually all local spending that I consider excludes direct transfers. Second, I do not observe heterogeneity in the multiplier with respect to variables related to MPCs. Finally, I show that fiscal spending in services and capital boost worker productivity and improve local socio-economical and health conditions. These findings point towards a mechanism of fiscal policy effectiveness that both relies on labor and demographic heterogeneity, and has at its core social-care which I show is largely responsible for the above-one average multiplier.

I rationalize these results via a model of heterogeneous labor and a shock that affects worker productivity by lowering their cognitive bandwidth. The social planner can, then, use public spending to increase the rate at which workers return to their normal, healthy state. I match the model to the data and show that the model-estimated local multipliers replicate the heterogeneity observed in the empirical results regarding the multiplier. The model highlights a mechanism through which returns to social-care spending change depending on how negatively affected a population is by conditions such as poverty, sickness, and the psychological toll of having to care for someone. I then use both the empirical estimates and the model to assess the current local fiscal policy in the UK. I show that there are significant gains from reducing fiscal misallocation, i.e. the opportunity cost from having more money spent in regions where the multiplier is lower, even if we keep current local public spending unchanged: addressing the misallocation since 2010 would have generated an additional 57.9 billion pounds from an optimally allocated central government grant, or 156 billion pounds in a scenario where government could reallocate total local spending. Using results from the model and if we allow for total spending to change, I show that an optimal local fiscal policy would increase yearly GDP growth by 0.5 percentage points on average. This gap relative to potential output has increased over time due to the estimated increase in the overall fiscal multiplier, which implies a larger optimal fiscal policy, and the reduction in real local spending in the UK.

The idea behind empirical estimates and the model is to show that local fiscal multipliers have significant heterogeneity. Results indicate that fiscal policy discussions should take into account the particular demographic and worker-level aspects of a locality before concluding on fiscal expansion or contraction. Given an average, country-wide local-level estimate of the fiscal multiplier, it is not clear whether a local authority should increase or decrease its spending. Moreover, my results suggest the possibility of gains from fiscal policy from a better allocation of local grants and/or local spending even if we keep aggregate expenditure constant. The role of fiscal misallocation between LADs only makes sense if we allow for local heterogeneity. An interesting venue for future research, then, is to consider local fiscal spending in a dynamic setting where current spending affects local parameters which, in turn, may change future fiscal multipliers. The social planner should, then, target not only static gains from optimal fiscal policy but also future increases in the multiplier, two goals that might be at odds and provide an interesting area to assess trade-offs.

References

Anderson, Emily, Atsushi Inoue, and Barbara Rossi, "Heterogeneous Consumers and Fiscal Policy Shocks," *Journal of Money, Credit and Banking*, 2016, *48* (8), 1877–1888.

Auerbach, Alan J. and Yuriy Gorodnichenko, "Measuring the Output Responses to Fiscal Policy," *American Economic Journal: Economic Policy*, May 2012, *4* (2), 1–27.

Auerbach, Alan, Yuriy Gorodnichenko, Peter B. McCrory, and Daniel Murphy, "Fiscal multipliers in the COVID19 recession," *Journal of International Money and Finance*, 2022, *126*, 102669.

Basso, Henrique S. and Omar Rachedi, "The Young, the Old, and the Government: Demographics and Fiscal Multipliers," *American Economic Journal: Macroeconomics*, October 2021, *13* (4), 110–41.

Berge, Travis, Maarten De Ridder, and Damjan Pfajfar, "When is the fiscal multiplier high? A comparison of four business cycle phases," *European Economic Review*, 2021, *138*, 103852.

Boehm, Christopher E., "Government Spending and Durable Goods," CESifo Working Paper Series 6244, CESifo 2016.

Borusyak, Kirill, Peter Hull, and Xavier Jaravel, "Quasi-Experimental Shift-Share Research Designs," *The Review of Economic Studies*, 2021, *89* (1), 181–213.

Brandao-Roll, Julio, Maarten Ridder, Simona Hannon, and Damjan Pfajfar, "The Fiscal Multiplier of Education Expenditures," 2024.

Brinca, Pedro, Hans A. Holter, Per Krusell, and Laurence Malafry, "Fiscal multipliers in the 21st century," *Journal of Monetary Economics*, 2016, *77*, 53–69. "Inequality, Institutions, and Redistribution"held at the Stern School of Business,New York University,April 24-25, 2015.

Burton, Wayne, Chin-Yu Chen, Alyssa Schultz, and Dee Edington, "The Impact of Allergies and Allergy Treatment on Worker Productivity," *Journal of Occupational and Environmental Medicine*, 02 2001, *43*, 64–71.

Burton, Wayne N., Alan Morrison, and Albert I. Wertheimer, "Pharmaceuticals and Worker Productivity Loss: A Critical Review of the Literature," *Journal of Occupational and Environmental Medicine*, 2003, *45* (6), 610–621.

Caldara, Dario and Christophe Kamps, "The Analytics of SVARs: A Unified Framework to Measure Fiscal Multipliers," *The Review of Economic Studies*, 2017, *84* (3), 1015–1040.

Capek, Jan and Jesus Crespo Cuaresma, "We just estimated twenty million fiscal multipliers," *Oxford Bulletin of Economics and Statistics*, 2020, *82* (3), 483–502.

Carroll, Christopher, Jiri Slacalek, Kiichi Tokuoka, and Matthew N. White, "The distribution of wealth and the marginal propensity to consume," *Quantitative Economics*, 2017, *8* (3), 977–1020.

Chernozhukov, Victor and Christian Hansen, "Instrumental variable quantile regression: A robust inference approach," *Journal of Econometrics*, 2008, *142* (1), 379–398.

Chodorow-Reich, Gabriel, "Geographic Cross-Sectional Fiscal Spending Multipliers: What Have We Learned?," *American Economic Journal: Economic Policy*, May 2019, *11* (2), 1–34.

_ , Laura Feiveson, Zachary Liscow, and William Gui Woolston, "Does State Fiscal Relief during Recessions Increase Employment? Evidence from the American Recovery and Reinvestment Act," *American Economic Journal: Economic Policy*, 2012, *4* (3).

Christiano, Lawrence, Martin Eichenbaum, and Sergio Rebelo, "When Is the Government Spending Multiplier Large?," *Journal of Political Economy*, 2011, *119* (1), 78–121.

Corsetti, Giancarlo, André Meier, Gernot J. Müller, and Michael B. Devereux, "What determines government spending multipliers?," *Economic Policy*, 2012, *27* (72), 521–565.

Fishback, Price and Valentina Kachanovskaya, "The Multiplier for Federal Spending in the States During the Great Depression," *The Journal of Economic History*, 2015, *75* (1), 125–162.

Gechert, Sebastian, "What fiscal policy is most effective? A meta-regression analysis," *Oxford Economic Papers*, 2015, *67* (3), 553–580.

Gibbons, Stephen and Wenjie Wu, "Airports, access and local economic performance: evidence from China," *Journal of Economic Geography*, 2019, *20* (4), 903–937.

_ , Teemu Lyytikäinen, Henry G. Overman, and Rosa Sanchis-Guarner, "New road infrastructure: The effects on firms," *Journal of Urban Economics*, 2019, *110*, 35–50.

Goetzel, Ron, Ronald Ozminkowski, Kevin Hawkins, Shaohung Wang, and Wendy Lynch, "Health, Absence, Disability, and Presenteeism Cost Estimates of Certain Physical and Mental Health Conditions Affecting U.S. Employers," *Journal of occupational and environmental medicine / American College of Occupational and Environmental Medicine*, 05 2004, *46*, 398–412.

Goldsmith-Pinkham, Paul, Isaac Sorkin, and Henry Swift, "Bartik Instruments: What, When, Why, and How," *American Economic Review*, August 2020, *110* (8), 2586–2624.

Ilzetzki, Ethan, Enrique G. Mendoza, and Carlos A. Végh, "How big (small?) are fiscal multipliers?," *Journal of Monetary Economics*, 2013, *60* (2), 239–254.

Kaplan, Greg and Giovanni L. Violante, "Microeconomic Heterogeneity and Macroeconomic Shocks," *Journal of Economic Perspectives*, August 2018, *32* (3), 167–94.

Kaur, Supreet, Sendhil Mullainathan, Suanna Oh, and Frank Schilbach, "Do Financial Concerns Make Workers Less Productive?," Working Paper 28338, National Bureau of Economic Research 2021.

Morita, Hiroshi, "On the relationship between fiscal multipliers and population aging in Japan: Theory and empirics," *Economic Modelling*, 2022, *108*, 105772.

Muratori, Umberto, Pedro Juarros, and Daniel Valderrama, "Heterogeneous Spending, Heterogeneous Multipliers," 2023, (2023/052).

Nakamura, Emi and Jon Steinsson, "Fiscal Stimulus in a Monetary Union: Evidence from US Regions," *American Economic Review*, March 2014, *104* (3).

Pappa, Evi, "The Effects of Fiscal Shocks on Employment and the Real Wage," *International Economic Review*, 2009, *50* (1), 217–244.

Pragidis, I.C., P. Tsintzos, and B. Plakandaras, "Asymmetric effects of government spending shocks during the financial cycle," *Economic Modelling*, 2018, *68*, 372–387.

Ramey, Valerie A., "Ten Years after the Financial Crisis: What Have We Learned from the Renaissance in Fiscal Research?," *Journal of Economic Perspectives*, May 2019, *33* (2), 89–114.

— **and Sarah Zubairy**, "Government Spending Multipliers in Good Times and in Bad: Evidence from US Historical Data," *Journal of Political Economy*, 2018, *126* (2), 850–901.

Riera-Crichton, Daniel, Carlos A. Vegh, and Guillermo Vuletin, "Procyclical and countercyclical fiscal multipliers: Evidence from OECD countries," *Journal of International Money and Finance*, 2015, *52*, 15–31.

Schilbach, Frank, Heather Schofield, and Sendhil Mullainathan, "The Psychological Lives of the Poor," *American Economic Review*, May 2016, *106* (5), 435–40.

Schultz, Alyssa and Dee Edington, "Employee Health and Presenteeism: A Systematic Review," *Journal of occupational rehabilitation*, 10 2007, *17*, 547–79.

Shoag, Daniel, "The Impact of Government Spending Shocks: Evidence on the Multiplier from State Pension Plan Returns ," Working Paper 2016.

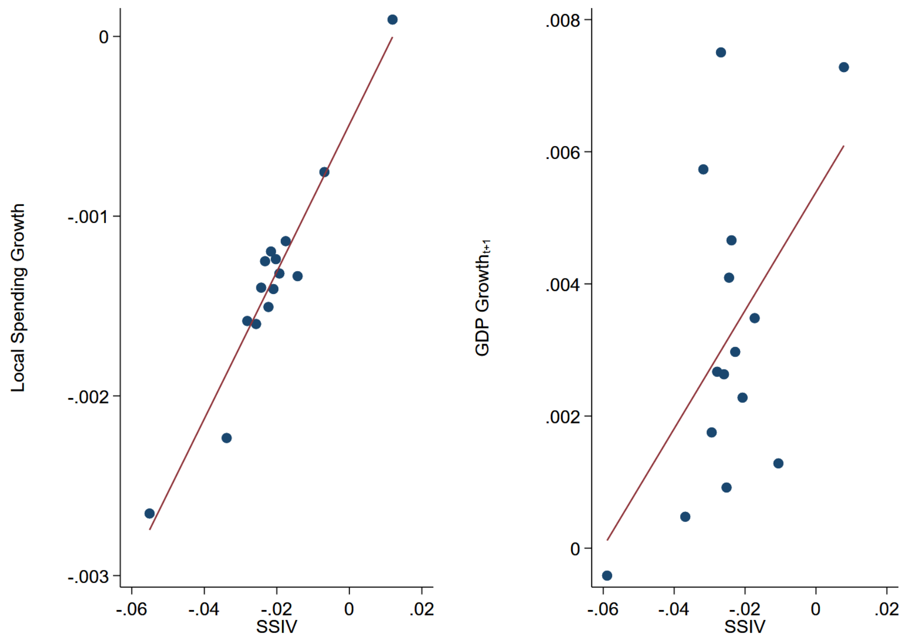
Yoshino, Naoyuki and Hiroaki Miyamoto, "Declined effectiveness of fiscal and monetary policies faced with aging population in Japan," *Japan and the World Economy*, 2017, *42* (C), 32–44.

Òscar Jordà and Alan M. Taylor, "The Time for Austerity: Estimating the Average Treatment Effect of Fiscal Policy," *The Economic Journal*, 2016, *126* (590), 219–255.

A Appendix

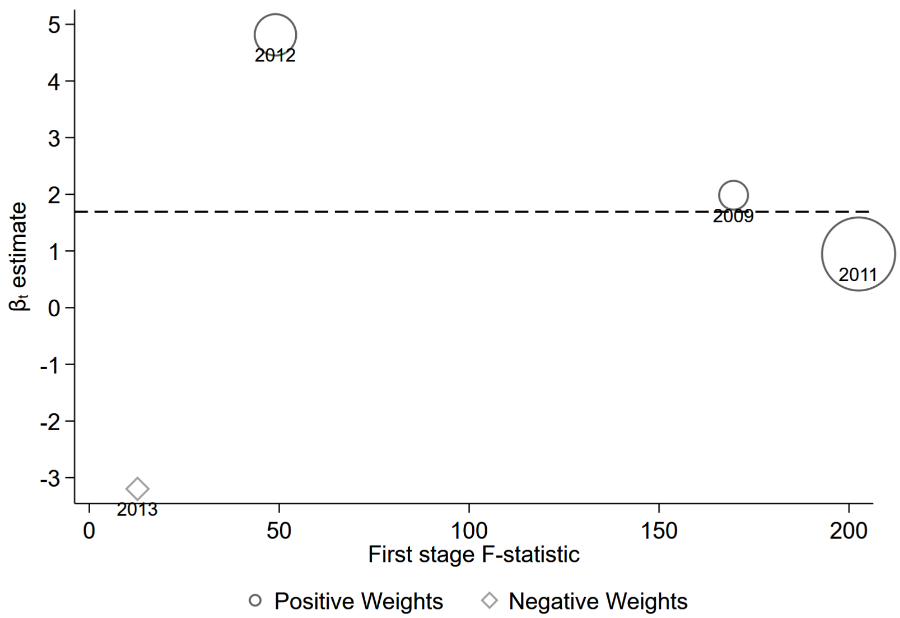
A.1 Tables and Figures

Figure A1: *First-Stage (left) Binned Scatter Plot and Reduced Form (right) Binned Plot*



Notes: Variables correspond to the residual of regressing each one on location and year fixed-effects. SSIV was multiplied by a factor of 1000 for clarity.

Figure A2: *Rotemberg Weights: Heterogeneity of $\hat{\beta}_t$.*



Just-identified coefficient estimates $\hat{\beta}_t$ and first-stage F-statistics are calculated using the specification of column (4) in Table 1. The horizontal dashed line indicates the benchmark estimate in Table 1 calculated using the SSIV. The size of the points is scaled by the magnitude of the respective Rotemberg weight. The figure excludes instruments with first-stage F-statistic below 10.

Figure A3: *Local Spending Breakdown*

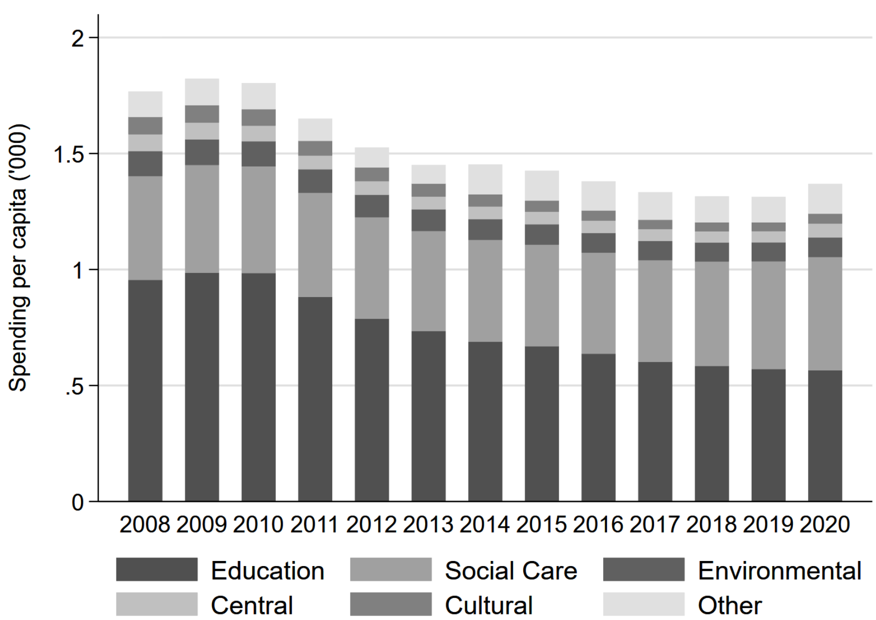


Figure A4: *Average Expected Local Fiscal Multiplier*

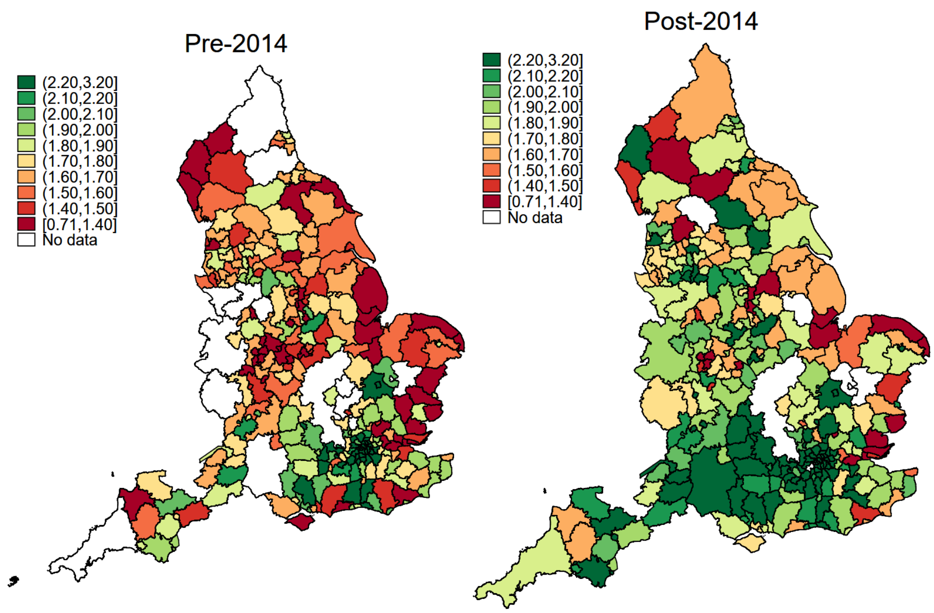


Figure A5: *Optimal Spending and Optimal to Actual Spending Ratio (London)*

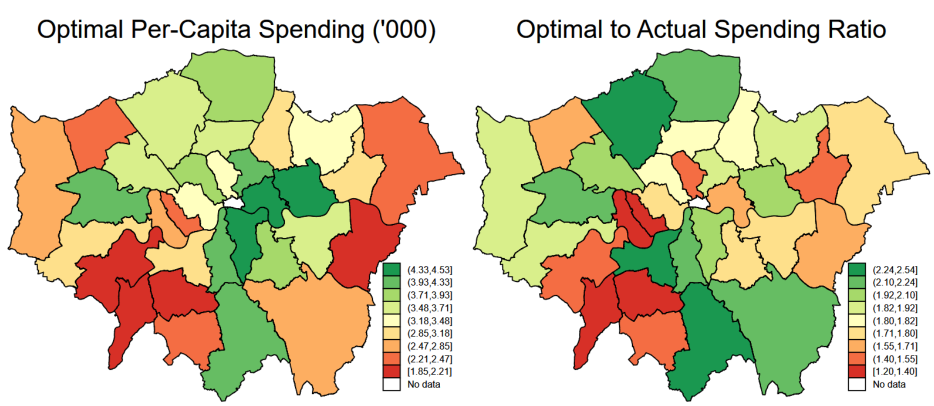


Figure A6: *Optimal to Actual Spending Ratio and Grant Allocation*

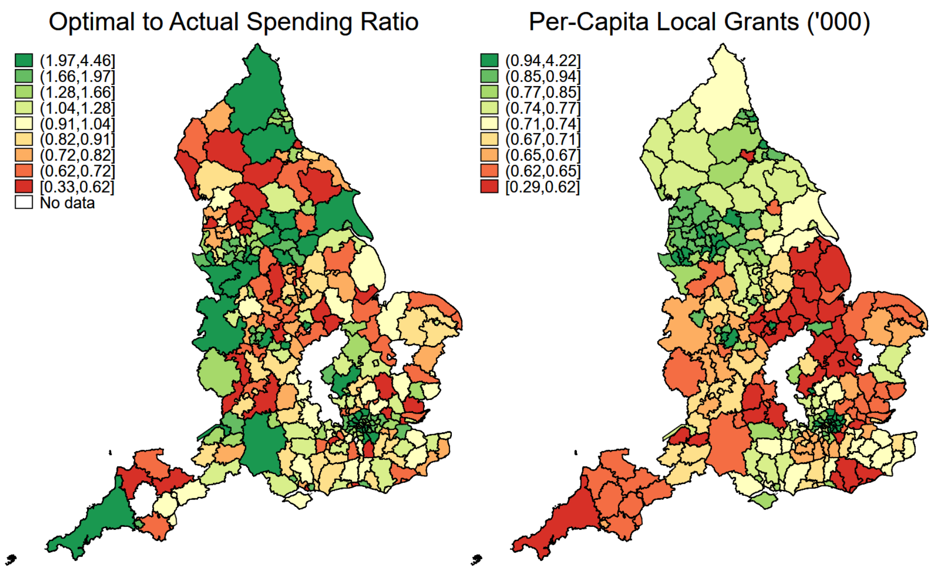


Table A.1: Summary Statistics

	Mean	St. Dev.	Obs	Min	Max
GDP Per-Capita Growth (%)	.46	4.15	3235	-23.07	35.11
Spending Per-Capita Growth (%)	-.16	.33	3235	-1.64	3.97
Grant Share of GDP (%)	2.89	1.28	3235	.21	8.4
National Growth in Grants (%)	-.08	.11	3235	-.35	.06
PC Grants Outside AEF ('000)	.42	.21	3235	.1	1.62
High School Share (%)	53.7	9.77	3235	25.3	82.3
Unemployment Rate (%)	5.91	2.71	3232	1	21.53
Median Age	41.27	4.72	3235	28.9	54.27
Child Poverty Rate (%)	16.81	6.74	3235	4.77	50.9
Share Receiving Transfers (%)	24.54	5.76	3235	.63	45.34
Average Full-Time Wage	17.56	3.48	3230	11.26	45.81
Per-Capita LAD Reserves ('000)	.33	.14	3235	.06	1.5
PC Non-Domestic Funds ('000)	.25	.13	3235	.05	.93
Average Council Tax ('000)	.66	.55	3235	.12	1.73
Economic Inactivity Per-Capita	.29	.04	3235	.14	.49
Share Inactives WWJ (%)	23.55	6.29	3235	0	48.77
Anxiety Level	2.92	.33	2658	1.75	4.19
Share Employed Failed GCSE (%)	7.65	2.24	2906	1.65	16.84
60-to-20th Wage Ratio	1.7	.14	3229	1.31	2.71
Per-Capita DALY	1.21	.17	3235	.75	2.05

Table A.2: Local Spending Fiscal Multiplier Estimates (Different Specifications)

	GDP_{t+1}									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Multiplier	1.738**	1.648**	1.635	1.856*	2.247**	1.769	1.789**	1.714**	3.017***	2.878***
	(0.805)	(0.795)	(0.992)	(1.036)	(0.908)	(1.183)	(0.790)	(0.790)	(0.912)	(0.892)
N	3,235	3,235	2,938	2,938	3,235	3,235	3,235	3,235	3,235	3,235
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Council FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls		Yes		Yes		Yes		Yes		Yes
Outside AEF Grants	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Robust F-statistic	101.8	110.6	102.1	123.2	94.8	63.2	101.0	109.8	75.5	75.4

Notes: Specifications: (1)-(2): weighted regression; (3)-(4): two-year lagged shares; (5)-(6): first-period fixed shares; (7)-(8): dependent variable is the one-year ahead yearly change in real local GDP per-capita over current real GDP per-capita; (9)-(10): SSIV using shares by spending category. Main regressor corresponds to growth in real local authority total service expenditure per-capita. GDP_{t+1} corresponds to growth one period ahead. Local-level controls (first-period interacted with year fixed effects in columns (5) and (6), one-year lagged for the rest): share of NVQ3 awards (equivalent to a high-school diploma), unemployment rate, median age, child poverty rate, average full-time wage, per-capita number of people receiving central government benefits (for Disability Living Allowance, Incapacity Benefits, Housing Benefit, Universal Credit, Personal Independence Payment, and Child Benefit) where each claimant counts by the number of individual benefits they receive, dummies for the political party controlling the local council, LAD reserves per-capita, per-capita amount of funds from non-domestic rates, and average council tax. Outside AEF Grants is the per-capita amount of all grants outside the AEF which are not included in the SSIV. Standard errors are clustered by counties for non-metropolitan districts and by individual LAD for the rest. *, **, *** denote significance at 10%, 5%, and 1% levels, respectively.

Table A.3: Local Spending Fiscal Multiplier Estimates (TTWA level)

	GDP_{t+1}			
	(1)	(2)	(3)	(4)
Multiplier	1.925*	1.513	1.852*	1.583
	(0.996)	(0.971)	(1.025)	(1.023)
N	1,317	1,317	1,317	1,317
Time FE	Yes	Yes	Yes	Yes
Council FE	Yes	Yes	Yes	Yes
Controls		Yes		Yes
Outside AEF Share			Yes	Yes
Robust F-statistic	29.2	33.4	27.0	30.9

Notes: Main regressor corresponds to growth in real local authority total service expenditure per-capita. GDP_t corresponds to local GDP per-capita growth and GDP_{t+1} to growth one period ahead. Local-level controls (one-year lagged): share of NVQ3 awards (equivalent to a high-school diploma), unemployment rate, median age, child poverty rate, average full-time wage, per-capita number of people receiving central government benefits (for Disability Living Allowance, Incapacity Benefits, Housing Benefit, Universal Credit, Personal Independence Payment, and Child Benefit) where each claimant counts by the number of individual benefits they receive, LAD reserves per-capita, per-capita amount of funds from non-domestic rates, and average council tax. Outside AEF Grants is the per-capita amount of all grants outside the AEF which are not included in the SSIV. Standard errors are clustered by counties for non-metropolitan districts and by individual LAD for the rest. *, **, *** denote significance at 10%, 5%, and 1% levels, respectively.

Table A.4: Local Total Spending Fiscal Multiplier Estimates

	GDP_{t+1}							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Total Spending	1.390**	1.320**	1.427**	1.346**				
	(0.549)	(0.557)	(0.562)	(0.566)				
Total Spending_{2y}					1.015***	1.062***	1.066***	1.089***
					(0.337)	(0.341)	(0.338)	(0.343)
N	3,235	3,235	3,235	3,235	2,938	2,938	2,938	2,938
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Council FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls		Yes		Yes		Yes		Yes
Outside AEF Grants			Yes	Yes			Yes	Yes
Robust F-statistic	81.2	79.6	83.5	82.7	96.6	97.5	99.1	104.3

Notes: Main regressors correspond to growth in real local authority total expenditure (services and capital combined) per-capita. Subscript $2y$ indicates that the change is over two years. GDP_{t+1} corresponds to local GDP per-capita growth one period ahead. Local-level controls (one-year lagged in columns (1)-(4) and two-year lagged in columns (5)-(8)): share of NVQ3 awards (equivalent to a high-school diploma), unemployment rate, median age, child poverty rate, average full-time wage, per-capita number of people receiving central government benefits (for Disability Living Allowance, Incapacity Benefits, Housing Benefit, Universal Credit, Personal Independence Payment, and Child Benefit) where each claimant counts by the number of individual benefits they receive, dummies for the political party controlling the local council, LAD reserves per-capita, per-capita amount of funds from non-domestic rates, and average council tax. Outside AEF Grants is the per-capita amount of all grants outside the AEF which are not included in the SSIV. Standard errors are clustered by counties for non-metropolitan districts and by individual LAD for the rest. *, **, *** denote significance at 10%, 5%, and 1% levels, respectively.

Table A.5: Shift-Share Balance Test

	DSG Share	GDP Growth	Within AEF Share	GDP Growth
	(1)	(2)	(3)	(4)
High School level	0.003	-0.076*	0.018	-0.063*
	(0.015)	(0.039)	(0.013)	(0.037)
Unemployment Rate	0.037***	-0.040	0.032***	-0.038
	(0.012)	(0.024)	(0.010)	(0.023)
Age (median)	-0.115	-0.281*	-0.075	-0.358**
	(0.113)	(0.165)	(0.101)	(0.162)
Child Poverty Rate	-0.117**	0.003	-0.123**	-0.010
	(0.058)	(0.055)	(0.050)	(0.050)
Independent	0.239	-0.015	0.357*	-0.052
	(0.186)	(0.121)	(0.198)	(0.107)
Liberal Democrat	-0.076	-0.202*	-0.128*	-0.232**
	(0.077)	(0.104)	(0.069)	(0.095)
Labour	0.090	-0.149*	-0.005	-0.124*
	(0.059)	(0.088)	(0.059)	(0.073)
No Control	-0.030	-0.074	-0.027	-0.073
	(0.031)	(0.059)	(0.035)	(0.049)
Transfers (People)	-0.006	0.207***	0.055	0.241***
	(0.063)	(0.058)	(0.042)	(0.066)
Wage	-0.121***	0.061	-0.112***	0.038
	(0.043)	(0.106)	(0.037)	(0.097)
Reserves	0.059*	-0.047	0.050	-0.038
	(0.031)	(0.030)	(0.031)	(0.028)
Non-Domestic Rates	0.037	0.050	0.070	0.037
	(0.050)	(0.057)	(0.047)	(0.052)
Council Tax	-0.450	0.859*	-0.228	0.693*
	(0.275)	(0.453)	(0.249)	(0.416)
N	2,949	2,949	3,235	3,235
R-squared	0.937	0.431	0.943	0.420
Time FE	Yes	Yes	Yes	Yes
Council FE	Yes	Yes	Yes	Yes

DSG Share is the ratio between the Dedicated Schools Grant and local authority spending. Within AEF Share is the ratio between the sum of all grants inside the AEF and local authority spending. Regressors are one-year lagged in columns (2) and (4). Standard errors are clustered by LAD. *, **, *** denote significance at 10%, 5%, and 1% levels, respectively.

Table A.6: Local Spending Fiscal Multiplier Estimates (Overidentified Shares-Only Specification)

	GDP_{t+1}			
	(1)	(2)	(3)	(4)
Multiplier	0.906	0.495	0.907	0.519
	(0.658)	(0.633)	(0.661)	(0.639)
N	3,235	3,235	3,235	3,235
Time FE	Yes	Yes	Yes	Yes
Council FE	Yes	Yes	Yes	Yes
Controls		Yes		Yes
Outside AEF Grants			Yes	Yes
Robust F-test	21.8	21.9	22.1	22.9
J-test, p-val	0.03	0.02	0.03	0.02

Notes: Estimates are calculated using the Limited Information Maximum Likelihood (LIML) estimator. Main regressor corresponds to real local authority total service expenditure per-capita growth. GDP_{t+1} corresponds to growth one period ahead. Local-level controls (one-year lagged): share of NVQ3 awards (equivalent to a high-school diploma), unemployment rate, median age, child poverty rate, average full-time wage, per-capita number of people receiving central government benefits (for Disability Living Allowance, Incapacity Benefits, Housing Benefit, Universal Credit, Personal Independence Payment, and Child Benefit) where each claimant counts by the number of individual benefits they receive, dummies for the political party controlling the local council, LAD reserves per-capita, per-capita amount of funds from non-domestic rates, and average council tax. Outside AEF Grants is the per-capita amount of all grants outside the AEF which are not included in the SSIV. Standard errors are clustered by counties for non-metropolitan districts and by individual LAD for the rest. *, **, *** denote significance at 10%, 5%, and 1% levels, respectively.

Table A.7: Summary of Rotemberg Weights

Panel A: Negative and positive weights

	Sum	Mean	Share
Negative	-0.040	-0.020	0.037
Positive	1.040	0.116	0.963

Panel B: Correlations

	$\hat{\alpha}_t$	g_t	$\hat{\beta}_t$	$\hat{F}_t$	Var(s_{t-1})
$\hat{\alpha}_t$	1				
g_t	-0.832	1			
$\hat{\beta}_t$	0.120	-0.010	1		
$\hat{F}_t$	0.816	-0.417	0.163	1	
Var(s_{t-1})	0.561	-0.282	0.027	0.628	1

Panel C: Top 4 Rotemberg weight years

	$\hat{\alpha}_t$	Share of LADs with negative grant grw.	g_t	$\hat{\beta}_t$	95 % CI
2011	0.670	0.969	-3.506	0.947	(-1.40,3.10)
2012	0.213	0.896	-2.498	4.814	(1.00,10.80)
2009	0.102	0.021	0.625	1.984	(0.10,4.20)
2013	-0.030	0.587	-0.716	-3.197	(-14.00,5.30)

Panel D: Estimates of $\hat{\beta}_t$ for positive and negative weights

	$\hat{\alpha}$-weighted sum	Share of overall $\hat{\beta}_t$	Mean
Negative	-0.088	-0.052	7.203
Positive	1.780	1.052	-9.511

Note: This table reports the summary statistics about the Rotemberg weights using the specification of column (8) in Table 1. Panel A reports the sum, mean, and share of weights for both positive and negative weights. Panel B reports the correlations between the weights ($\hat{\alpha}_t$), the national changes to grants (g_t), the just-identified coefficients estimates calculated for each year ($\hat{\beta}_t$), the first-stage F-statistic of the year shares ($\hat{F}_t$), and the variation in the year shares across LADs (Var(s_{t-1})). Panel C reports the top four years according to the Rotemberg weights (annual shock g_t was multiplied by a factor of 1000 for clarity). The 95% confidence interval is the weak instrument robust confidence interval using the method from Chernozhukov and Hansen (2008) over a range of -20 to 20. Panel D reports how the values of $\hat{\beta}_t$ vary with the positive and negative Rotemberg weights.

Table A.8: Heterogeneity in the Effect of Local Fiscal Spending by Spending Category

	GDP_{t+1}		
	(1)	(2)	(3)
Education Spending Share	-0.763*		
	(0.414)		
Social Care Spending Share		1.116*	
		(0.597)	
Planning Spending Share			3.344*
			(1.850)
N	3,235	3,235	3,235
Time FE	Yes	Yes	Yes
Council FE	Yes	Yes	Yes
Controls	Yes	Yes	Yes
Outside AEF Grants	Yes	Yes	Yes
Spending Category	Yes	Yes	Yes
Robust F-test	13.1	14.4	9.7

Notes: Main regressors correspond to change in the spending-specific share of total local spending in services. GDP_t corresponds to local GDP per-capita growth and GDP_{t+1} to growth one period ahead. Local-level controls (one-year lagged): share of NVQ3 awards (equivalent to a high-school diploma), unemployment rate, median age, child poverty rate, average full-time wage, per-capita number of people receiving central government benefits (for Disability Living Allowance, Incapacity Benefits, Housing Benefit, Universal Credit, Personal Independence Payment, and Child Benefit) where each claimant counts by the number of individual benefits they receive, dummies for the political party controlling the local council, LAD reserves per-capita, per-capita amount of funds from non-domestic rates, and average council tax. Outside AEF Grants is the per-capita amount of all grants outside the AEF which are not included in the SSIV. Spending Category controls for the one-year lagged share of spending in transportation, education, social-care, housing, cultural, planning, central, and environmental. Standard errors are clustered by counties for non-metropolitan districts and by individual LAD for the rest. *, **, *** denote significance at 10%, 5%, and 1% levels, respectively.