The Small Business Channel of the Matching Multiplier

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Abstract

This paper proposes that small businesses comprise a mechanism which potentially explains why the unequal incidence of economic recessions increases the aggregate marginal propensity to consume (MPC). Patterson (2021) demonstrates the existence of the matching multiplier, where the matching of high MPC individuals with more cyclical jobs amplifies the aggregate MPC. I hypothesize that this matching is mediated through small business activity and show how the matching multiplier can be decomposed into a small business channel and a residual term. Using regional variation during the COVID-19 pandemic, I identify this channel and find that although such channel exists, its magnitude is too small to explain a large matching multiplier. This null result suggests one fewer argument which could justify macroeconomic stabilization policies targeting small businesses.

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1 Introduction

The COVID-19 pandemic precipitated an unprecedented economic recession in the U.S. A pronounced focus of the policy response to the virus has been the damage suffered by small businesses. In the U.S. context, small businesses belong disproportionately to the service sector, which was hit harder than the goods-producing sector due to the limitations on in-person activity during the pandemic. Given that small businesses have generated over 40% of U.S. GDP over the past decade and comprise nearly 50% of employment,[1] it seems reasonable for policies aimed at stabilizing the macroeconomy to target small businesses. Notably, the U.S. government launched the Paycheck Protection Program to support small business employees and to prevent small businesses closures due of lockdowns and social distancing measures. This paper proposes a theoretical channel for why small business activity might matter for aggregate activity and inequality. While this channel exists in the data, I find that the magnitude of the channel is far too small to meaningfully explain aggregate fluctuations in consumption and output.

A central question about recessions is how aggregate consumption will respond to a drop in aggregate output. The key theoretical quantity for this question is the aggregate marginal propensity to consume (MPC). In classical Keynesian analysis, a multiplier applies to government stimulus so that a dollar of stimulus yields $1/(1 - MPC)$ in realized spending. A vast literature has attempted to estimate MPCs using a variety of methodologies and have typically found large MPCs at the household level, often around 20%, which implies a classical Keynesian multiplier of 1.25. In structural models, however, it has been difficult until recently to generate large individual MPCs that result in meaningful aggregate MPCs because of the tendency for high-wealth agents, who matter more for aggregate dynamics, to have low MPCs.

Patterson (2021) theorizes a mechanism through which the aggregate MPC can be large in spite of low MPCs for high-wealth agents and demonstrates empirically that this mechanism matters. She shows that the aggregate MPC can be decomposed into two terms, the earnings-weighted average MPC with the earnings-weighted covariance of an individual's MPC and the elasticity of their earnings to aggregate output. While the first term reflects the fact that the

[1] See US Small Business Administration, Office of Advocacy (2019) and US Small Business Administration, Office of Advocacy (2020).

MPCs of high-income households, which are typically lower, matters more than low-income households on average, the presence of high MPC but low-income individuals may still result in a large aggregate MPC through the covariance term if high MPC individuals tend to have more cyclical earnings. Patterson (2021) empirically confirms in U.S. data that the covariance between MPCs and earnings elasticities is positive and sizable, a phenomenon that she terms the *matching multiplier*. Through the matching multiplier, inequality among individuals can cause an unequal incidence of adverse aggregate shocks and thereby amplify recessions.

This paper contributes to our understanding about why this matching multiplier might exists. In particular, I propose that small business activity is a mediating channel for the matching of high MPC individuals to individuals with cyclically sensitive earnings. Intuitively, because small businesses may be more cyclical,[2] agents whose earnings depend on small business activity may have more cyclical earnings in general, and these same agents may also have high MPCs (e.g. servers at a local restaraunt). I show that the covariance Patterson (2021) estimates can be further decomposed into a term representing the matching effect due to small businesses and a residual term. To identify the contribution of small business activity to the multiplier, I use regional variation in MPCs, earnings elasticities, and small business revenue elasticity to aggregate output.

Using data from Chetty et al. (2020)'s Economic Tracker database, Lewis et al. (2020)'s Weekly Economic Index (WEI), the Bureau of Labor Statistics (BLS), and the U.S. Census Bureau, I construct a weekly panel dataset of observations by county (FIPS) code from January 2020 to January 2021. With this dataset, I impute regional MPCs using Patterson (2021)'s estimates of individual MPCs and estimate the elasticities needed to calculate the contribution of small business activity to the matching multiplier. I find that the elasticity of regional income to regional small business revenue rises with the regional MPC by 4.33% per unit increase in MPC, while the elasticity of regional small business activity to aggregate output falls with the regional MPC by 13.2% per unit increase in MPC. With these estimates of the elasticity, I compute that the contribution of small businesses to the matching multiplier is -1.57×10^{-6}.

[2] A variety of mechanisms lead small businesses to be more cyclical. Liquidity constraints and other hurdles to financing may be one reason (see Begenau and Salomao (2018) and Caglio et al. (2021)), with small businesses being less likely to survive downturns as a result. Crouzet and Mehrotra (2020) also finds that small firms are more cyclical than large firms.

Contrary to my initial hypothesis, the magnitude of the contribution to the matching multiplier from small business activity is far too small to explain the relatively large covariance Patterson (2021) identifies. In fact, my estimate of the contribution from small business activity is negative, implying that the matching between MPCs and small business activity dampens the aggregate MPC.

These results suggest a more limited role for small businesses in determining aggregate fluctuations. If my initial hypothesis had been true, then there could be an argument for directing fiscal stimulus and social insurance programs during economic downturns toward small businesses. By targeting regions whose small business revenue is more cyclical, stabilization policies would funnel dollars indirectly toward regions with higher MPCs and thereby generate larger consumption responses than otherwise. It would also indirectly support high MPC workers who are disproportionately impacted by the recession. However, since this is not the case, my paper suggests that there is one fewer argument which could justify macroeconomic stabilization policies targeting small businesses like the Paycheck Protection Program.

1.1 Related Literature

My paper contributes to the literature on firm size in business cycles. Several studies have focused on the importance of large firms to aggregate fluctuations. Gabaix (2011) demonstrates that shocks to individual firms can cause aggregate fluctuations when the firm size distribution is sufficiently fat-tailed. Carvalho and Grassi (2019) validates this theory with a general equilibrium model in which aggregate fluctuations emerge from only firm-level shocks and particularly from large firms. Crouzet and Mehrotra (2020) empirically find that large firms comprise major drivers of aggregate fluctuations, but large firms are also less cyclically sensitive than small firms. This cyclicality among small firms is also associated with more cyclical stock returns according to Perez-Quiros and Timmermann (2000). In contrast to this literature which focuses on large firms, my paper focuses on small businesses. Although I find evidence of a relationship between small business activity and aggregate consumption, the relationship is not large enough to be meaningful at the aggregate level, consistent with the literature on firm size and business cycles.

My research design follows previous work and exploits heterogeneity in regional dynamics to understand aggregate phenomena. To identify the economic impact of wealth effects on consumption and employment, Mian et al. (2013), Mian and Sufi (2014), and Chodorow-Reich et al. (2021) use cross-sectional variation across geographic regions. Similarly, to understand employment dynamics during and after the Great Recession, Beraja et al. (2019) and Jones et al. (forthcoming) combine aggregate data with regional data to identify structural macroeconomic models. Beraja et al. (2019) shows that nominal wage rigidity explains far less of the dynamics in aggregate employment when regional business cycles are heterogeneous. Jones et al. (forthcoming) also use a model with heterogeneous regional business cycles and find that while household deleveraging slowed the recovery from the Great Recession, it does not explain the aggregate employment behavior. To identify the aggregate impact of fiscal policy, Nakamura and Steinsson (2014) estimate local multipliers by exploiting geographic variation in military spending and map these results to an aggregate multiplier with a theoretical model.

My paper also relates to the recent literature focusing on the covariance between heterogeneous MPCs and other quantities to explain macroeconomic behavior. Auclert (2019) decomposes the response of aggregate consumption to a monetary policy shock into three channels, which depend on the covariance between household MPCs and objects like net nominal positions and unhedged interest rate exposures. Bilbiie (2019) analytically establishes that cyclicality in risk and inequality are two separate channels that affect the mapping from microeconomic consumption behavior to aggregate consumption responses. The fall in aggregate demand in a recession is amplified when inequality is countercyclical, meaning that in recessions low-income agents lose disproportionately more of their income. In the context of Patterson (2021) and my paper, the covariance between household MPCs and the exposure of their earned income to aggregate risk is a measure of cyclical inequality, with a positive covariance indicating countercyclical inequality.

Additionally, my dataset covers economic activity in the U.S. during the COVID-19 pandemic, hence my work provides some insight into the pandemic's economic effects and the policy response to them. A well-documented consequence of the pandemic has been the unequal incidence of its economic effects. For example, Adams-Prassl et al. (2020) show that women and less educated workers have been more affected by the crisis while Fairlie et al. (2020) identify a disproportionate impact on minorities during COVID-19's first wave. Chetty et al. (2020) find that small business revenue fell most in high-income zip codes, where consumption fell drastically, and the Paycheck Protection Program targeting small businesses had a minimal effect on employment, increasing it by only 2%. Granja et al. (2020) also find that the employment effects of the Paycheck Protection Program were limited and point to implementation issues as significant causes. If my paper shows high MPC individuals are matched with cyclical jobs through the small business channel, then such finding supports policies that aim to aid small businesses and thereby indirectly support their employees. If the small business channel is not salient, then support to small businesses will not be sufficient to address the unequal incidence recession has on high MPC workers.

In contrast to policies aimed at small businesses, the expansion of unemployment insurance (UI) benefits during the pandemic witnessed far greater success. As a measure of the magnitude of the UI benefit extension, Ganong et al. (2020) demonstrate that a large majority of UI-eligible workers received benefits which replaced above 100% of their lost wages. Using administrative data from the J.P. Morgan Chase Institute, Ganong et al. (2021) find that the UI benefits expansion caused a substantial increase in household consumption with minimal negative effects on employment, in contrast to predictions by standard job search models. Thus, UI benefits succeeded at providing macroeconomic stabilization without substantially raising unemployment.

Finally, my paper relates to the large literature which attempts to estimate MPCs from income shocks using microeconomic data. Many research designs have been employed toward this end. Several studies exploit tax rebates and stimulus payments to identify household MPCs. For example, Johnson et al. (2006) and Parker et al. (2013) examine the behavior of household consumption to fiscal stimulus in response to the 2001 and 2008 recessions. Other papers like Blundell et al. (2008) and Crawley and Kuchler (2020) utilize panel data to estimate how households change their consumption after permanent and/or transitory income shocks. These studies find substantial MPCs (typically around 20%) out of transitory income shocks, which are much larger than that predicted by the permanent income hypothesis.

Despite extensive evidence of large MPCs at the microeconomic level, researchers have only recently discovered plausible mechanisms to generate large aggregate MPCs. Older work (e.g. Krusell and Smith (1998)) failed to produce aggregate MPCs that matched estimates from micro data because it was common to model high MPC agents as poor households, who comprise too little of aggregate consumption since they do not earn much. Kaplan et al. (2014) show that this problem can be reconciled by distinguishing between liquid and illiquid wealth. Households can be simultaneously wealthy and borrowing constrained if most of their wealth is held in illiquid assets like housing. Such households will still exhibit high MPCs because their liquid wealth is very low and do not have substantial liquidity available to them, as Kaplan and Violante (2014) show in a structural model. My work relates to this literature in that it studies another mechanism, the small business channel of the matching multiplier, to produce large aggregate MPCs.

The rest of the paper is organized as follows. Section 2 theoretically defines the small business channel of the matching multiplier. Section 3 details the data imputations I employ to construct the dataset. Section 4 delineates the regression specifications I use, reports the estimates from my regressions, and discusses their implications. Section 5 concludes.

2 Defining the small business channel of the matching multiplier

This paper is motivated by the concept of the matching multiplier demonstrated in Patterson (2021), where the author shows that workers with high MPCs match with more cyclical jobs, and this covariance is large enough to increase the aggregate MPC by 30%. Previous literature has found that small businesses tend to be more cyclical in a number of dimensions, such as their financing strategies and their revenue. I explore a potential mechanism for why a matching between high MPC workers and cyclical jobs occurs: regional small business activity. While my paper's analysis is relatively agnostic about the exact reasons why small business activity is a potential mechanism, one intuitive reason is that high MPC workers may tend to work for small businesses and are therefore more exposed to business cycles due to the cyclicality of the firms for which they work. Following the simplified two-period model in Patterson (2021), I decompose the covariance between individual MPCs and the elasticities of individual incomes to aggregate movements into a small business channel and other channels.

In this simple model, I assume all economic output is consumed by workers such that the market clearing condition $Y = C$ holds, where Y is aggregate output, and C is aggregate consumption. There is no capital income or business profits, and aggregate income is composed solely of labor income. Let total consumption in county j be $c_j(E_j \mid \theta_j)$.[3] To allow matching between individuals with small businesses within a county, I introduce total earned income E as a function of small business vitality S, measured by indicators such as number of small businesses in a region or regional small business revenue and other economic factors O. Both regional indicators are functions of the aggregate output Y including endogeneous variables that are affected by aggregate output. Lastly, regional consumption is a function of regional income and other exogeneous factors θ that affects consumption. Thus, the function

$$c_j(E_j(S_j(Y), O_j(Y)) \mid \theta_j)$$

describes consumption in county j.

From the market clearing condition $Y = \sum_j c_j(E_j(S_j(Y), O_j(Y)) \mid \theta_j)$, where aggregate output equals aggregate income, I can obtain the aggregate MPC that captures how aggregate demand responds to an additional unit of output. To calculate the MPC, I first define several elasticities that are used to derive the small business channel to simplify the notations. Two notable ones are π_j which is the elasticity of regional income to small business activity (later empirically measured as small business revenue) and ε_j which is the elasticity of small business activity to aggregate economic output.

$$\pi_j = \frac{\partial E_j}{\partial S_j}\frac{S_j}{E_j}, \quad \varepsilon_j = \frac{\partial S_j}{\partial Y}\frac{Y}{S_j}, \quad \omega_j = \frac{\partial E_j}{\partial O_j}\frac{O_j}{E_j}, \quad \eta_j = \frac{\partial O_j}{\partial Y}\frac{Y}{O_j}. \tag{1}$$

Using these elasticities, I may decompose the aggregate MPC into the following proposition.

[3] More generally, j denotes any region. To avoid clutter, I use the concrete label of a county.

Proposition 2.1. *Under the assumptions stated previously, the aggregate MPC can be written as*

$$\frac{dC}{dY} = \underbrace{\mathbb{E}_{E_j/Y}\left[\frac{\partial C_j}{\partial E_j}\right]}_{\textit{Average MPC}} + \underbrace{\mathrm{Cov}_{E_j/Y}\left(\frac{\partial C_j}{\partial E_j}, \varepsilon_j \pi_j\right)}_{\textit{Small business channel}} + \underbrace{\mathrm{Cov}_{E_j/Y}\left(\frac{\partial C_j}{\partial E_j}, \eta_j \omega_j\right)}_{\textit{Other channels}} \tag{2}$$

Proposition 2.1 states that the aggregate MPC can be decomposed into three parts that are weighted by regional income: (i) average regional MPC; (ii) the covariance between the regional MPC and regional income elasticity to aggregate output through small business activities; and (iii) covariance between regional MPC and regional income elasticity through other channels. The first covariance captures the matching between regions with heterogeneous MPCs to regions with different cyclically sensitive earnings through the small business channel. This covariance is the main focus of this paper. A detailed derivation of Proposition 2.1 can be found in Appendix A.

If small businesses play a major role in mediating the matching of high MPC regions to regions with cyclically sensitive earnings as described in Patterson (2021) and in determining aggregate fluctuations, we expect to see the covariance in proposition 2.1 to be positive and significantly large. As we shall see, I estimate that the product $\varepsilon_j \pi_j$ is negative.

Thus, a positive covariance then implies that high MPC regions tend to feature either regional income that is not sensitive to small business activity ($\pi_j \approx 0$) or acylical small business revenue ($\varepsilon_j \approx 0$). Insensitive regional income could happen when small business activity is not an important determinant of income in regions with high MPCs. Acyclical small business revenue could be a characteristic of regions with high MPCs, perhaps due to consumption shifting toward small businesses during downturns because of supply chain disruptions or because they provide cheaper alternatives to products sold by large businesses.

Conversely, the covariance is negative if regions with high MPCs tend to be regions with small businesses that are more countercyclical and earnings that increase with small business activity or with small businesses that are more procyclical and earnings that decrease with small business activity. In the former case, countercyclical small business revenue may arise when the consumption shifting phenomenon mentioned earlier is sufficiently strong that revenue in fact rises during downturns rather than staying approximately constant. In the latter case, less small business activity could imply greater employment at larger firms, and such employment may provide higher pay on average, hence the inverse relationship between reagional small business activity and earnings.

3 Data imputation

To empirically estimate the covariance for the small business channel, I take advantage of the variation created by the COVID-19 recession and construct a weekly panel dataset of observations by county (FIPS) code from January 6, 2020 (week 2 of 2020) to January 29, 2021 (week 4 of 2021) for 1067 counties in the U.S. I draw from Chetty et al. (2020)'s Economic Tracker database from Opportunity Insights for data on small business revenue, from Lewis et al. (2020)'s Weekly Economic Index (WEI) for a weekly measure of GDP,[4] MPC coefficients for different demographics from Patterson (2021), and county demographics and income data from Bureau of Labor Statistics (BLS) and the U.S. Census Bureau. A full list of data used and their sources can be found in Appendix B.

In particular, the small business revenue data comes from Chetty et al. (2020)'s Economic Tracker database from Opportunity Insights. Due to data masking, the regional small business revenues are not at their actual levels, but are indexed to January 2020 and thus reflect seasonally adjusted changes (*Opportunity Insights Economic Tracker Data Documentation*, 2022). Figure 1 shows the plot for the interquartile range for the small business revenue changes in my data. The dots represents the median, the upper bar represents the 75th percentile, and the lower bar represents the 25th percentile. We can see that changes in small business revenue exhibit substantial cross-sectional dispersion across time, which will allow me to identify the elasticities of interest.

[4] As stated on the Federal Reserve Bank of New York's interactive page for the index, "the WEI represents the common component of ten daily and weekly series covering consumer behavior, the labor market, and production." While not an exact fit, the 13-week moving average WEI does approximate quarterly real GDP starting back in January 2008. At the same time, the index does not aim to predict quarterly real GDP as its primary target but rather focus on weekly variation in real economic activity. For this reason, it is an appropriate measure of aggregate output for my paper.

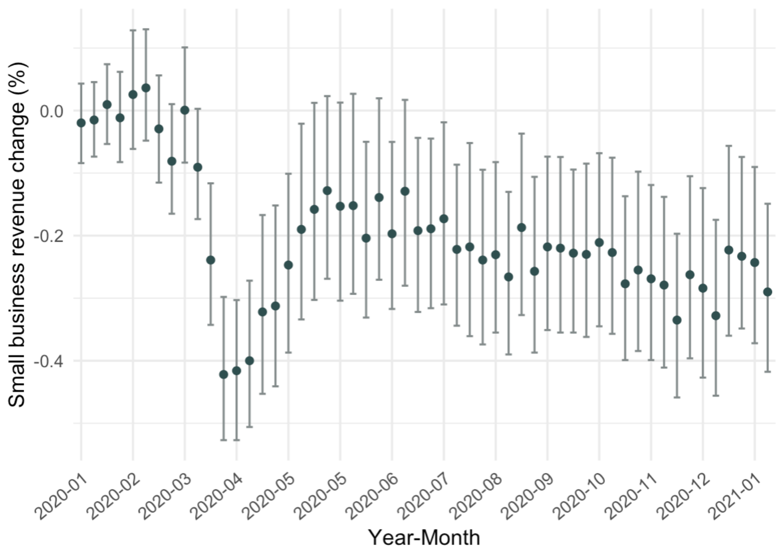

Figure 1: IQR plot of small business revenue change relative to January 2020.

Additionally, with the data I have available, I do not directly observe weekly variation in labor income, so I impute weekly labor income for all counties. I assume that the extensive margin matters the most for earned labor income. I obtain income variation at a weekly frequency by multiplying the average weekly earnings of the county by the employment rate and the total labor force number for that county. While the labor force size and average weekly earnings statistics are obtained at monthly frequencies, the employment rate time series are weekly. Thus, income variation in my dataset mostly comes from the extensive margin through variations in the employment rate.

To determine the magnitude of the small business channel, the key objects I need to estimate are the differential elasticity of income to small business revenue π_j, the elasticity differential of small business revenue to aggregate output ε_j, and the regional MPC: $\frac{\partial C_j}{\partial E_j}$. I impute the regional MPC by using the MPC coefficients estimated by Patterson (2021) (Table A7, PSID imputation) and data on regional demographics. For each county, I multiply the MPC coefficients for each demographic group with the share of the corresponding demographic group in that county and then sum up across the different demographic components. Following Patterson (2021)'s baseline specification, the dimensions along which I calculate heterogeneous MPCs in my data include the share of different income bins, share of female population, and share of Black population. Figure

2 shows the spatial distribution of the imputed MPCs by county. My imputation indicates that counties in the southern U.S. tend to have higher MPCs. Since many counties in the South have relatively larger Black populations, this result is consistent with Patterson (2021)'s finding that MPCs tend to be higher for Black individuals and low-income individuals.

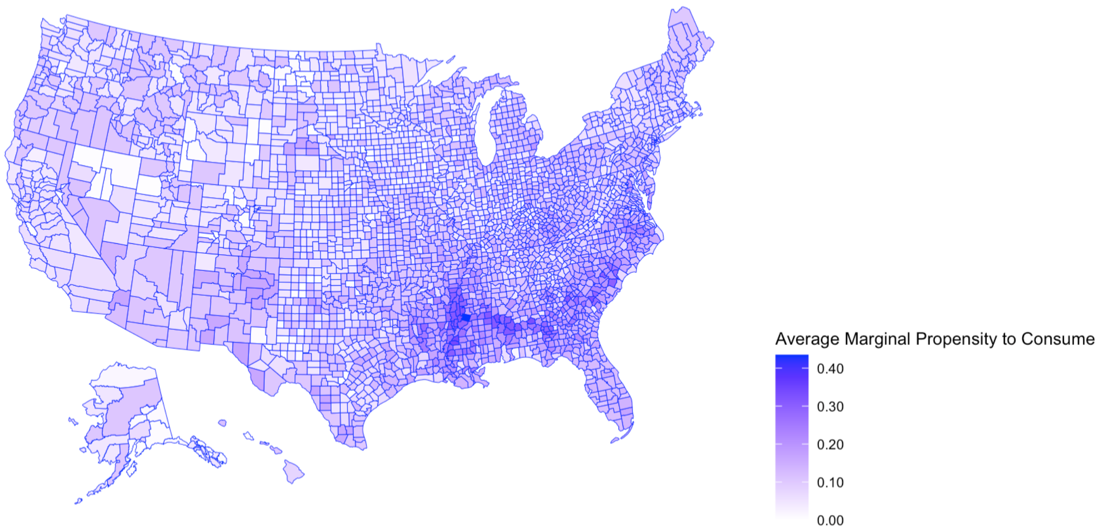

Figure 2: Spatial Distribution of Imputed MPCs by County

Lastly, Table 1 displays summary statistics for variables of interest in my data.

Statistic	N	Mean	St. Dev.
Annual individual income	51,935	44,963.9	6,223.5
Weekly county income	51,935	124,676,686.0	266,436,325.0
Weekly county income percentage change	50,950	0.000	0.03
County MPC	100,489	0.1	0.1
Weekly revenue percentage change	100,489	−0.005	0.2
Weekly GDP percentage change	100,489	−0.2	0.2
Num. of small business openings (rel. to Jan 2020)	66,690	0.5	0.8
COVID-19 death rate	100,489	−0.1	0.6

Table 1: This table reports summary statistics unconditional on time from week 2 of 2020 to week 4 of 2021. The income and MPC numbers are imputed using publicly available data from the BLS, U.S. Census Bureau, Economic Tracker, and Patterson (2021). The data on small businesses and COVID-19 are drawn from the Economic Tracker dataset. Finally, the weekly GDP percentage change is calculated from the WEI.

4 Empirical specifications and results

To compute the small business channel of the matching multiplier, I also need to estimate the elasticities π_j and ε_j. For the following specifications, I use j to indicate county-level variables, δ_t as a time fixed effect, α_j as a county fixed effect, and $X_{j,t}$ as other controls. I obtain ε_j, the elasticity of regional labor income to regional small business revenues, from the following regression:

$$\%\Delta E_{j,t} = \zeta_1 \widehat{MPC}_{j,t-1} \times \%\Delta S_{j,t} + \zeta_2 \widehat{MPC}_{j,t-1} + \zeta_3 \%\Delta S_{j,t} + \delta_t + \alpha_j + X_{j,t}\zeta_4 + \nu_{j,t}. \quad (3)$$

In equation (3), $\%\Delta E_{j,t}$ represents the percentage change in income, $\%\Delta S_{j,t}$ represents the percentage change in small business revenue in county j, and $\widehat{MPC}_{j,t-1}$ is the estimated lag MPC to avoid any contemporaneous effects with non-lagged MPCs when estimating the small business channel of the matching multiplier. Note that the MPC may change over time because the imputed MPC depends on income bins, and there is income variation in my dataset.

I allow for heterogeneity in this elasticity from variation in MPCs by interacting lagged MPCs with $\%\Delta S_{j,t}$, the percentage difference in small business revenue in equation (3), since I am primarily interested in the heterogeneity in the elasticity π_j which covaries with a county's MPC. Counties in the regression are weighted by their regional income shares because we care about the share of dollars earned in the economy, not the number of counties.

Additionally, because I have a panel dataset, to control for unobserved omitted variables, my preferred specification includes time and county fixed effects. The rapid development of COVID variants and variation in state public health measures makes the inclusion of fixed effects particularly important to correctly estimate the elasticity. The county fixed effect controls for unobservables that vary across counties but are constant over time, such as public sentiment toward state public health measures like resistance to masking policies. The time fixed effect controls for unobservables that equally apply to all counties but vary over time, such as the development of new variants during the pandemic. These unobservables undoubtedly affect people's consumption behavior and small business revenue and decisions to remain open.

Additional control variables includes changes in small business openings and new COVID death rates. Both variables vary across counties and time. The number of small business openings affects small business revenue in a region and affects regional labor earning if a significant number of people who work for small businesses lost their jobs during the pandemic. New COVID death rates is also a comparable if not better indicator for the infection rate, when testing was limited in the beginning of the pandemic. High death and infection rates reduce people's consumption and their willingness to work, particularly when many still lack the antibodies against COVID-19.

From this estimation, I can obtain the elasticity of regional labor income to small business revenue for different counties as $\widehat{\pi}_{j,t} = \zeta_1 \widehat{MPC}_{j,t-1} + \zeta_3$. The elasticity $\pi_{j,t}$ has a time subscript now because lagged regional MPC may vary over time due to income variation. The time dependence was omitted in Section 2. The expectations and covariances in Proposition 2.1 will remain the same because they are unconditional quantities.

Table 2 reports the estimation results for the elasticity of regional income to regional small business revenue. The key coefficients are those for the interaction term in the first row and for the revenue percentage change in the third row. Across the specifications, I obtain a positive effect on the interaction between lagged MPC and the percentage change in small business revenue, hence an increase in a county's MPC increases its elasticity of earnings to small business activity. My preferred specification in Table 2 is column (4) which includes time and county fixed effects to control for unobserved omitted variables. Based on that specification, a unit increase in the MPC raises the elasticity of county earnings to county small business revenue by 4.33%. Further, the coefficient on the main effect for the percentage change in small business revenue is nearly zero and insignificant. Thus, when calculating $\pi_{j,t}$, I set the main effect to zero and compute $\widehat{\pi}_{j,t} = \zeta_1 \widehat{MPC}_{j,t-1}$. The mean and the standard deviation for $\widehat{\pi}_{j,t}$ are presented in Table 4.

Subsequently, I estimate the elasticity of regional small business revenue to aggregate output through the following regression:

$$\%\Delta S_{j,t} = \beta_1 \widehat{MPC}_{j,t-1} \times \%\Delta Y_t + \beta_2 \widehat{MPC}_{j,t-1} + \delta_t + X_{j,t}\beta_3 + \mu_{j,t} \tag{4}$$

	Weekly income percentage change			
Model:	(1)	(2)	(3)	(4)
Variables				
Lag MPC × Revenue %Δ	0.0044	0.0605**	0.0253	0.0433**
	(0.0276)	(0.0270)	(0.0250)	(0.0212)
Lag MPC	0.0385***	0.0224***	0.2887***	0.1787***
	(0.0038)	(0.0033)	(0.0124)	(0.0114)
Revenue %Δ	0.0093***	-0.0003	-0.0052***	-0.0001
	(0.0011)	(0.0012)	(0.0011)	(0.0010)
New COVID-19 death rate		-0.0006***	0.0005*	-0.0006**
		(0.0002)	(0.0003)	(0.0003)
Num. of small business openings		-0.0011	0.0784***	0.0027
		(0.0011)	(0.0036)	(0.0029)
(Intercept)	-0.0013***			
	(0.0002)			
Time fixed effect	No	Yes	No	Yes
County fixed effect	No	No	Yes	Yes
Fit statistics				
Standard-Errors	Robust	Robust	County	County
Observations	50,950	37,224	37,224	37,224
R^2	0.00502	0.39291	0.08927	0.41316
Within R^2		0.00203	0.07245	0.01471

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 2: This table presents the estimation results for the elasticity of county income to county small business revenue. Standard errors are reported in parentheses below the coefficient estimates. All observations are weighted by income, as in Patterson (2021). The dependent variable in all of the displayed regressions is the weekly income percentage change calculated using data from the BLS and the U.S. Census Bureau. Columns (1)-(2) use heteroskedasticity-consistent standard errors while columns (3)-(4) use clustered standard errors on the county level to correct for correlation among observations within each county. Column (1) regresses the dependent variable on only lagged MPC, the percentage change in small business revenue, and their interaction. The coefficient of interest is the interaction coefficient. While not significant in (1), the sign is positive. Once controls are added in (2), the sign becomes significant at the 5% confidence level. The sign remains positive in column (3) after adding the county fixed effect and remains significant in column (4) after adding both time and county fixed effects. My preferred specification is column (4) with both time and county fixed effects to control for county-invariant and time-invariant unobservables.

The coefficient of interest is β_1. Given this coefficient, I will be able to calculate the elasticity of regional small business revenue to aggregate output for each region by $\varepsilon_{j,t} = \beta_1 \times \widehat{MPC}_{j,t-1}$. $\%\Delta Y$ is the percentage change in aggregate output, measured by the WEI. As before, $\%\Delta Y$ is interacted with the lagged MPCs to avoid any contemporaneous effect and to allow for heterogeneity in the elasticity due to variation in MPCs across counties. Here, I only use the time fixed effect to control for factors that are the same across states but varies over time, and I do not need to include a county fixed effect because the regressor of interest is a variable measured at the national level. I exclude the main effect for $\%\Delta Y$ from the specification because it is absorbed by the time fixed effect.

I report my estimation results for the elasticity of regional small business revenue to aggregate output in Table 3. The key coefficient of interest is the interaction term in the first row. Across the specifications, the coefficient on the interaction between lagged MPC and the percentage change in aggregate output is negative. Therefore, an increase in a county's MPC decreases its elasticity of small business revenue to aggregate output. Since I utilize regional variation to identify this elasticity, my econometric design partials out any general equilibrium effects, an identification challenge Wolf (2021) studies. My results suggest that in partial equilibrium, a fall in aggregate output implies an increase in small business revenue, which could be explained by consumption shifting from large businesses to small businesses in times of macroeconomic distress particularly that cuased by COVID-19.

My preferred specification here is column (2), which includes time fixed effects and the additional covariates in $X_{j,t}$ but omits the county fixed effects. As stated before, the reason is that the regressor of interest is a national variable. However, I present column (3) in Table 3 which includes county fixed effects to check that the inclusion of these fixed effects do not substantially change the coefficient in column (2). Based on the specification in column (2), a unit increase in the MPC decreases the elasticity of county small business revenue to aggregate output by -13.2%. Using the estimated result, I obtain the mean and the standard deviation for $\varepsilon_{j,t}$ and presented them in Table 4.

	Weekly revenue percentage change		
Model:	(1)	(2)	(3)
Variables			
Lag MPC × Weekly GDP percentage change	-0.0310	-0.1320***	-0.1365***
	(0.0243)	(0.0446)	(0.0447)
Lag MPC	0.0401**	-0.0292	0.1939***
	(0.0163)	(0.0179)	(0.0384)
Weekly GDP percentage change	0.0429***		
	(0.0012)		
New COVID-19 death rate		-0.0007	0.0012
		(0.0010)	(0.0009)
Num. of small business openings		0.0871***	0.3185***
		(0.0061)	(0.0114)
(Intercept)	-0.0030***		
	(0.0008)		
Time fixed effect	No	Yes	Yes
County fixed effect	No	No	Yes
Fit statistics			
Standard-Errors	Robust	Robust	County
Observations	98,569	66,690	66,690
R^2	0.01915	0.07468	0.08882
Within R^2		0.00486	0.01703

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 3: This table presents the estimation results for the elasticity of county small business revenue to aggregate output. Standard errors are reported in parentheses below the coefficient estimates. The dependent variable in all of the displayed regressions is the weekly percentage change in small business revenue calculated using data from the Economic Tracker database. Columns (1)-(2) use heteroskedasticity-consistent standard errors while column (3) is clustered on the county level to control for correlation among observations within each county. Column (1) regresses the dependent variable on only lagged MPC, the percentage change in aggregate output, and their interaction. The coefficient of interest is the interaction coefficient. While not significant in (1), the sign is negative. Once controls and time fixed effects are added in (2), the sign becomes significant at the 1% confidence level. The sign remains significantly negative in column (3) after adding the county fixed effect. My preferred specification is column (2) because the regressor of interest (aggregate output) is a variable on the national level. Note that the main effect for $\%\Delta Y$ is excluded because it is absorbed by the time fixed effect.

Statistic	N	Mean	St. Dev.
Income elasticity ($\hat{\pi}_{j,t}$)	98,569	0.003	0.002
Small business revenue elasticity ($\hat{\varepsilon}_{j,t}$)	98,569	-0.01	0.01

Table 4: This table presents the mean and the standard deviation of estimated elasticities using estimated coefficients from Equation 3 and Equation 4.

Finally, I calculate the earnings-weighted unconditional covariance between regional MPCs and the products of the two estimated elasticities:

$$\text{Cov}_{E_j/Y}(\widehat{MPC}_{j,t}, \hat{\pi}_{j,t}\hat{\varepsilon}_{j,t}) = \sum_{t=1}^{T}\sum_{j=1}^{N} \frac{E_{j,t}}{\sum_{t=1}^{T}\sum_{j=1}^{N} E_{j,t}} (\widehat{MPC}_{j,t} - \overline{MPC})(\hat{\pi}_{j,t}\hat{\varepsilon}_{j,t} - \overline{\pi\varepsilon}), \quad (5)$$

where T is the number of time periods, N the number of counties. This quantity is the small business channel I am looking for in Proposition (2.1). Using my estimates of $MPC_{j,t}$, $\pi_{j,t}$, and $\varepsilon_{j,t}$, I find that the covariance is -1.57×10^{-6}. This number is both far too small to amplify the aggregate MPC by a quantitatively meaningful amount and the opposite sign than I hypothesized.

Discussion These results contribute another piece of evidence that small businesses have a limited role in determining aggregate fluctuations. The granularity perspective (e.g. Gabaix (2011), Carvalho and Grassi (2019)) on the role of firm size focuses on the simple fact that large firms comprise a bigger share of economic output. Even if small businesses are more cyclical in their production activity and differ from large firms in their financing strategies,[5] their small size prevent them from having a large influence to the business cycles. This paper's research design studies a distinct matching mechanism for small businesses to contribute to business cycles. This mechanism relates to the network perspective on how aggregate fluctuations origin (see Acemoglu et al. (2012), Acemoglu et al. (2017), Baqaee and Farhi (2019), and Baqaee and Farhi (forthcoming)). Complementarities created by the network structure comprising an aggregate economy can be interpreted as a matching of certain sectors in such a way that they amplify sector-specific shocks into larger aggregate fluctuations.

This paper's result guides future policy aimed at stabilizing macroeconomic dynamics. If aggregate consumption falls because high MPC workers are matched to jobs whose sensitivity to aggregate output depends strongly on regional small business activity, as I had initially hypothesized, then an expansion of policies directing fiscal stimulus and social insurance toward small businesses during downturns could dampen fluctuations. Such an expansion would, all else

[5] Caglio et al. (2021) and Begenau and Salomao (2018) find that the credit options and choices by small firms are significantly different from large firms. For example, loans to small firms typically have higher interest rates and shorter maturities. Further, small firms choose more procyclical financing policies.

equal,[6] reduce the elasticity of small business activity to aggregate output and thus mitigate the subsequent consumption decline.

More broadly, this work connect to the increasing recognition among researchers that inequality shapes the impact of recessions at the macroeconomic level, hence social insurance programs addressing drivers of inequality may warrant expansion. My results suggest that the small business channel of the matching multiplier does not matter quantitatively. While alternative mechanisms may still justify policies like the Paycheck Protection Program, I find that the matching multiplier does not provide favorable evidence for them. In contrast, other policy responses, such as those that aim to directly support workers who are disproportionately affected by a recession, might prove more effective.

5 Conclusion

This paper proposes a theoretical channel for why small business activity may contribute to the aggregate MPC and thus to aggregate fluctuations. Although I find that this channel exists in the data, the magnitude is too small to explain a meaningful share of the matching multiplier conceived by Patterson (2021). This result is consistent with previous literature establishing that despite the higher cyclicality of small firms, their size is too small to matter for aggregate fluctuations. Further, to the extent that inequality matters for business cycles, small businesses do not appear to be the mechanism through which inequality determines macroeconomic dynamics.

Instead, future research dissecting the mechanisms behind the matching multiplier ought to focus on large firms, different industrial sectors, or other channels to understand why inequality amplifies recessions. For example, high MPC workers' earnings might match with cyclical jobs because large firms or specific sectors tend to employ many high MPC workers. Since shocks to large firms appear to drive a substantial portion of the variation in aggregate fluctuations, even though these firms are not as cyclical as smaller ones, because of their size, pass-through of firm shocks to workers' earnings might still have a quantitatively large effect.

[6] Crucially, this prediction assumes that agents would not endogenously respond to an expansion in countercyclical aid to small businesses in such a way that they do not increase their consumption.

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Appendices

A Proof of Proposition 2.1

First, define the additional elasticity

$$\gamma_j = \frac{\partial E_j}{\partial Y}\frac{Y}{E_j},$$

which is the earnings elasticity for region j.

I obtain the aggregate MPC by taking the total derivative of aggregate consumption.

$$\begin{aligned}
MPC = \frac{dC}{dY} &= \sum_j \left(\frac{\partial c_j}{\partial E_j}\frac{\partial E_j}{\partial S_j}\right)\frac{\partial S_j}{\partial Y} + \sum_j \left(\frac{\partial c_j}{\partial E_j}\frac{\partial E_j}{\partial O_j}\right)\frac{\partial O_j}{\partial Y} \\
&= \sum_j \frac{S_j}{Y}\left(\frac{\partial C_j}{\partial E_j}\frac{\partial E_j}{\partial S_j}\right)\varepsilon_j + \sum_j \frac{O_j}{Y}\left(\frac{\partial C_j}{\partial E_j}\frac{\partial E_j}{\partial O_j}\right)\eta_j \\
&= \sum_j \frac{S_j}{Y}\varepsilon_j\left(\frac{E_j}{S_j}\frac{\partial C_j}{\partial E_j}\pi_j\right) + \sum_j \frac{O_j}{Y}\eta_j\left(\frac{E_j}{O_j}\frac{\partial C_j}{\partial E_j}\omega_j\right) \\
&= \sum_j \frac{E_j}{Y}\varepsilon_j\left(\frac{\partial C_j}{\partial E_j}\pi_j\right) + \sum_j \frac{E_j}{Y}\eta_j\left(\left[\frac{\partial C_j}{\partial E_j}\omega_j\right]\right) \\
&= \mathbb{E}_{E_j/Y}\left[\frac{\partial C_j}{\partial E_j}\pi_j\varepsilon_j\right] + \mathbb{E}_{E_j/Y}\left[\frac{\partial C_j}{\partial E_j}\eta_j\omega_j\right] \\
&= \mathbb{E}_{E_j/Y}\left[\frac{\partial C_j}{\partial E_j}\right]\mathbb{E}_{E_j/Y}\left(\pi_j\varepsilon_j\right) + \mathrm{Cov}_{E_j/Y}(\frac{\partial C_j}{\partial E_j}, \pi_j\varepsilon_j) \\
&\quad + \mathbb{E}_{E_j/Y}\left[\frac{\partial C_j}{\partial E_j}\right]\mathbb{E}_{E_j/Y}\left(\eta_j\omega_j\right) + \mathrm{Cov}_{E_j/Y}(\frac{\partial C_j}{\partial E_j}, \eta_j\omega_j) \\
&= \mathbb{E}_{E_j/Y}\left[\frac{\partial C_j}{\partial E_j}\right]\mathbb{E}_{E_j/Y}\left(\gamma_j\right) + \mathrm{Cov}_{E_j/Y}(\frac{\partial C_j}{\partial E_j}, \pi_j\varepsilon_j) + \mathrm{Cov}_{E_j/Y}(\frac{\partial C_j}{\partial E_j}, \eta_j\omega_j) \qquad (6)
\end{aligned}$$

Note here that the subscript E_j/Y indicates either a expectation or a covariance weighted by the earnings share. Because I assume all output is earned labor income, the earnings shares sum to one. The last line uses the fact that:

$$\gamma_j = \frac{Y}{E_j}\left(\frac{\partial E_j}{\partial S_j}\frac{\partial S_j}{\partial Y} + \frac{\partial E_j}{\partial O_j}\frac{\partial O_j}{\partial Y}\right) = \frac{Y}{E_j}\left(\frac{\partial E_j}{\partial S_j}\varepsilon_j\frac{S_j}{Y} + \frac{\partial E_j}{\partial O_j}\eta_j\frac{\partial O_j}{\partial Y}\right)$$
$$= \frac{S_j}{E_j}\frac{\partial E_j}{\partial S_j}\varepsilon_j + \frac{O_j}{E_j}\frac{\partial E_j}{\partial O_j}\eta_j = \varepsilon_j\pi_{ij} + \eta_j\omega_{ij} \tag{7}$$

It can be further demonstrated that:

$$\mathbb{E}_{E_j/Y}(\gamma_j) = \sum_j \gamma_j \frac{E_j}{Y} = \sum_i \frac{dE_j}{dY}\frac{Y}{E_j}\frac{E_j}{Y} = \sum_i \frac{dE_j}{dY} = \frac{d\sum_i E_j}{dY} = 1. \tag{8}$$

Therefore, the aggregate MPC is

$$\frac{dC}{dY} = \mathbb{E}_{E_j/Y}\left[\frac{\partial C_j}{\partial E_j}\right] + \mathrm{Cov}_{E_j/Y}(\frac{\partial C_j}{\partial E_j}, \pi_{jj}) + \mathrm{Cov}_{E_j/Y}(\frac{\partial C_j}{\partial E_j}, \eta_j\omega_j). \tag{9}$$

B Data Sources

Table 5: This table presents the data series used to construct the panel data used for the empirical analysis. Time period represents the time period selected.

Data Series	Frequency	Level	Source	Time period
Employment rate change (relative to Janurary 2020)	weekly	county	Opportunity Insight Economic Tracker	w1 2020 - w4 2021
Small business revenue change (relative to January 2020)	weekly	county	Opportunity Insight Economic Tracker	w1 2020 - w4 2021
Small business openings change (relative to January 2020)	weekly	county	Opportunity Insight Economic Tracker	w1 2020 - w4 2021
New COVID death rate	weekly	county	Opportunity Insight Economic Tracker	w1 2020 - w4 2021
Weekly economic index	weekly	national	Federal Reserve Bank of New York	w1 2020 - w4 2021
Employment number and labor force	monthly	county	U.S. Bureau of Labor Statistics - Local Area Unemployment Statistics	Jan2020 - Jan2021
Average weekly earning	monthly	county	U.S. Bureau of Labor Statistics - State and Metro Area Employment, Hours, & Earnings	Jan2020 - Jan2021
County population characteristics	annual	county	U.S. Census Bureau - Annual County Resident Population Estimates by Age, Sex, Race, and Hispanic Origin: April 1, 2010 to July 1, 2019	2019
Income	annual	county	U.S. Census Bureau - American Community Survey	2019

Note: w represents week.