Estimations of the impacts of the deaths from COVID-19 on per capita income and employment for men and women in NYC

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Abstract

Using data for 118 public use microdata areas (PUMA) of New York City for the period of November 2020 through June 2021, we find evidence that income reduced in response to deaths from the Coronavirus, while employment increased. Analysis reveals these results are similar for men, but not for women. We find more spatial correlation effects on women than on men, and we also find more negative shocks for women than for men. We interpret our results as evidence that men on average accepted declines in wage earnings, which generated an increase in their employment, while females did not accept declines in their earnings and probably changed or quit their jobs. The study cannot distinguish if these results are due to labor market discrimination against women or if they are the result of choices made by the different gender groups in the labor market.

Keywords: income, employment, COVID-19, spatial correlation.
JEL Classification: I15, J17, J16, D62, C23, R12.

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Resumen

Estimación de los impactos de las muertes por COVID-19 sobre el ingreso per capita y el empleo de hombres y mujeres en la Ciudad de Nueva York

Usando datos de 118 áreas de microdatos de uso público (PUMA, por sus siglas en inglés) de la Ciudad de Nueva York para el periodo de noviembre 2020 a junio 2021, se encuentra evidencia de que el ingreso se redujo en respuesta a las muertes por el COVID-19, mientras que el empleo se incrementó. El análisis revela que estos resultados son similares para los hombres pero no para las mujeres. Se encuentran más efectos de correlación especial para mujeres que para hombres y encontramos evidencia de que existieron más shocks negativos para mujeres que para hombres. Estos resultados se interpretan como evidencia de que en promedio los hombres aceptaron reducciones en ingreso, lo cual generó un aumento en su empleo, mientras que las mujeres no aceptaron reducciones en sus ingresos y probablemente cambiaron o renunciaron a sus empleos. El estudio no puede distinguir si estos resultados son debido a discriminación laboral en contra de la mujer o si son el resultado de las decisiones hechas por diferentes grupos de acuerdo a su género en el mercado laboral.

Palabras clave: ingreso, empleo, COVID-19, correlación espacial.
Clasificación JEL: I15, J17, J16, D62, C23, R12.

Introduction

As of September 2022, the COVID-19 pandemic has generated more than 6.5 million deaths worldwide and 1 million deaths in the United States (The New York Times, 2022). The pandemic required strong measures that restricted the movement of individuals and merchandises in many countries, generating a dramatic economic crisis in the entire world economy. The US GDP and employment experienced strong declines during 2020 (Congressional Research Service (CRS), 2021; Santacreu *et al.,* 2021) that required an important intervention from the part of the US government (CRS, 2021), which eventually generated a recovery in the US income and employment during 2021.

In the case of New York City, studies show a dramatic increase in the rate of unemployment during the months of the pandemic. The city lost thousands of jobs due to the economic crisis that followed the pandemic and by December 2020 it had not recovered all those job losses (Economic Development Quarterly (EDQ), 2021). Different authors have researched the economic impact of the pandemic for specific regions and cities (Gascon and Haas, 2020; Klein and Smith, 2021; Ravindranath, 2021), but few have used disaggregated census data at the neighborhood level to study the economic impacts of the pandemic on income and employment, especially in New York City, the epicenter region of this pandemic.

This article contributes to the literature by looking at the effects of COVID-19 on income and employment in the New York City Area. We relate deaths occurred in New York City between November 2020 and June 2021, with changes in income and employment between 2020 and 2019, as measured by the American Community Survey. Unlike other studies that look at deaths at county level[1] (Saffary *et al.,* 2020; McLaren, 2020), in this research we disaggregate deaths at a lower geographic unit. We use data at the Public Use Microdata Area (PUMA) level.[2] Data on deaths is obtained at zip code level from New York City Health (NYCH) (2022), and the data is then "*cross walked*" to PUMA level using coding procedures provided by Baruch College (Newman Lybrary, 2022) for the months of November 2020 to June 2021.[3]

By looking at a more disaggregated level we can study how the spatial correlation observed in the sample interacts with the estimated effects of the pandemic on income and employment rates for the entire population of New York City. The origin of such spatial correlation has different theoretical explanations. From the point of view of economic theory, spatial autocorrelation in economic outcomes may exist due to the existence of knowledge spillovers, the need for thick markets for specialized skills and the existence of backward and forward linkages

1 A county is an administrative or political subdivision of a state that consists of a geographic region with specific boundaries and some level of governmental authority.

2 A PUMA is a non-overlapping statistical geographical area that partitions each state or equivalent entity into geographic areas containing no fewer than 100,000 people each.

3 "Cross-walking" is a term used in the literature of data analysis that means the combination of two data sets around similarities or overlaps (Hai-Jew, 2019).

associated with large markets (Fujita *et al*., 1999). From the point of view of sociological theory, spatial autocorrelation is important for health outcomes because spatial concentration may be linked to structural racism (Hochschild 2016; Fuentes-Mayorga and Burgos, 2017; Kahn *et al*., 2020). Other explanations for the importance of spatial concentration refer to the epidemiological characteristics of COVID-19 (Zhu *et al*., 2021), or its relationship with air pollution found in metropolitan areas (Bossak and Andritsch, 2022).

Our study also compares how the negative effects of the pandemic vary between men and women, and whether the spatial correlation also varies by sex. We draw on research that has already established that there are different reasons for the existence of gaps by gender in economic outcomes, such as the effect of labor market discrimination, individual and group preferences (Azmat and Petrongolo, 2014), gender roles in which men and women are assigned or select themselves (Rice and Coates, 1995), and due to men and women different bargaining power in the labor market (Folbre, 2021). Other explanations for differences by gender in health outcomes are linked to biological (Takahashi *et al.,* 2020), and behavioral (Sasson, 2016; Tokuyama and Mao, 2021) factors affecting men and women. Other authors have also examined differences in deaths by gender (Boulgaurt, 2020) and attribute these to differences in the labor force participation, occupations, means of transportation (Garcia *et al*., 2021), as well as on the rates of vaccination experienced by men and women (Riley *et al.*, 2021). Drawing on this emerging literature, we further explore how death rates impacted the income and employment outcomes of men and women and how the spatial correlation effects varied by sex.

Our analysis is organized as follows: the first part reviews the literature on the impacts of COVID-19 on output and employment, as well as the policy measures taken to counteract the economic crisis brought in by the pandemic, the measurement of the economic impact of deaths, the importance of spatial concentration in health outcomes, and the differences in economic outcomes between men and women; the second part shows our empirical models used to calculate the economic impact of deaths on income and employment; the third part presents the data and results from empirical analyses; the fourth part presents the conclusions of the paper.

1. Theoretical considerations

1.1. The impact of COVID-19 on income and employment

US GDP is estimated to have declined by 3.4% during 2020, compared to 2019 (CRS, 2021); yet, during 2021, the US GDP has seen a recovery over its three first quarters (CRS, 2021). Employment in the US also showed a dramatic change during the period of March 2020 through February 2021, as during this period 115 million Americans suffered a lost in employment income and 37 million received unemployment benefits (CRS, 2021). Apparently, since October 2021, the situation has improved as only 2.7 million Americans have qualified to receive unemployment benefits, down from a peak observed in May 2020, when 25 million Americans qualified for unemployment benefits.

These reductions in output and employment were accompanied by reductions in industrial production, retail sales, declines in financial markets, disrupted trade flows and supply chains, as well as a strong decline in migration to the US (Economic Commission for Latin American Countries (ECLAC), 2020).

Reflecting the complexity of the global value chains that characterize many US industries, the disruption of the global value chains due to the pandemic and enforced lock down or isolation affected the decline in output and employment across all US industries (Santacreu *et al*., 2021).

Scholars have studied the effects of the Coronavirus by regions of the US. For example, Klein and Smith (2021) study six metropolitan areas in the US and find that cities concentrated in industries that were most affected by the pandemic, like those linked to tourism and the movement of people, suffered more than cities concentrated in industries less affected or which even benefited from the pandemic. Gascon and Haas (2020) study how COVID-19 temporarily affected the real estate market in cities like St. Louis, Memphis, Louisville, and Little Rock. They find that the pandemic affected sales and rents particularly during the Spring of 2020, but that by the end of 2020 the real estate market was at levels like those before the pandemic. Ravindranath (2021) finds how remote work has evolved during the pandemic in Richmond. She finds that remote work is not as high as it was during March 2020 and September 2020, but that it remains higher than it was before the pandemic, concluding that hybrid work is now the new reality for the US's workforce.

Statistical reports also indicate that in New York City between February and June of 2020 the unemployment rate went from 3.4% to 20.4%. In total, the city experienced a loss of 894 thousand jobs from February to April of 2020, recovering only 308 thousand jobs in the following seven months. Certain sectors have recovered more jobs than others. For example, construction recovered 72% of jobs lost and retail trade also gained back 55% of lost jobs (Economic Development Quarterly (EDQ), 2021).

Residents of New York City also experience other risk factors including high density, at first related to high infection rates, and later to a higher possibility of fighting the virus, since concentrated urban areas provided faster emergency responses to the crisis (EDQ, 2021). Studies have shown that the number of COVID-19 cases confirmed are linked to wealth, socioeconomic status, and levels of education. These results highlighted the existence of inequities in New York City (EDQ, 2021).

Studies in New York City have also demonstrated that the labor market sectors most affected include the higher education, tourism, and small business sectors. These studies have also pointed out that essential workers, those earning low wages and in occupations with high interaction with others have fared worse due to the pandemic (EDQ, 2021).

These results implied that the public policies implemented in New York City were focused on vulnerable industries and employees. The policies in New York City also prioritized industries that had the most impact on employment. Industries categorized as priorities were non-grocery retail, restaurants, social assistance, personal services, fitness and recreation business, laundromats and dry cleaners, repair workers for household appliances, taxi workers, hotels, and medical and dentist offices. Industries were defined as priority if they had low levels of cash on hand, many employees at small establishments; whether firms generated many jobs per $1M industry purchases or employed many essential workers. Among workers, policies targeted racial minorities, those experiencing severe rent-burdens, and low-income individuals (EDQ, 2021).

Economic measures taken by the US government in response to the pandemic included: i) measures that were directed towards specific key industries, ii) fiscal measures supporting the health sector, households, and firms, iii) fiscal deficits, iv) worker assistance programs, and v) monetary and prudential measures, including stimulus checks to workers with vulnerable immigration status (CRS, 2021). All these measures were designed to reduce the economic impact of the pandemic.

1.2. Measuring the economic impact of diseases

There are two main methods to estimate the economic impact of a disease. The first one is called the value of lost output (Alkire *et al.,* 2018) which consists in estimating how the disease affected output through its impact on labor supply and investment. The method attempts to calibrate macroeconomic models that look at the direct impact of the disease on labor supply and its effect on investment. Borrowing from these approaches, our analysis uses as an approximation a reduced form approach, where we estimate how deaths due to COVID-19 reduced median income in the NYC region (neighborhood level by the Census' PUMA) controlling for the level of labor supply in each spatial location and how the labor supply is distributed among occupations. We carry out a similar estimation for the effect of COVID-19 on employment at the PUMA level.

The second one, measures the value of lost welfare (Alkire *et al.,* 2018) which consists in estimating how welfare was reduced due to the Coronavirus, based on the statistical value of a life (Viscusi and Aldi, 2003), which attempts to capture market and non-market losses such as forgone leisure time of the value placed on good health.

For some authors, the impact of the disease could also include externalities (Kuhn *et al*., 2011), economies of scale and economies of scope (Keith and Prior, 2014), as well as public goods (Anderson and Treich, 2011). Some authors argue that it should also include the human suffering that it generates (Anderson, 2013).

1.3. The role of spatial concentration on health and economic outcomes

According to Fujita *et al*. (1999) spatial autocorrelation in economic outcomes arises due to knowledge spillovers, the need for thick markets for specialized skills and the existence of backward and forward linkages associated with large markets. These different factors contribute to generate agglomeration economies, leading certain urban centers to persistently accumulate more economic activities than others and establish differences from other rural centers on the long run.

In the case of spatial correlations and health outcomes, Hochschild (2016) and Fuentes-Mayorga and Burgos (2017) argue that there exists a nexus between structural racism and the spatial distribution of the health outcomes of individuals. Structural racism is defined as "the totality of ways in which societies foster racial discrimination through mutually reinforcing systems of housing, education, employment, earnings, benefits, credit, media, health care, and criminal justice. These patterns and practices in turn reinforce discriminatory beliefs, values, and distribution of resources" (Bailey *et al.*, 2017:1457). Under this explanation, poor and racialized individuals experience constraints in changing their spatial location or neighborhoods to improve their life chances. Consequently, spatial concentration reproduces the lower life chances and limited access and quality of health services, as well as lower quality housing for these individuals. These forms of structural inequalities intersect to eventually cause lower health outcomes among Hispanic and other historically racialized minorities compared to the rest of the US population (Hochschild, 2016; Fuentes-Mayorga and Burgos, 2017).

Evidence of the significance of spatial correlation has been documented by Saffary *et al*. (2020). They claim that the spatial correlation between deaths and ethnic groups is not homogeneous, since they find a spatial correlation for the share of Non-Hispanic Blacks, while no such correlation exists for the Hispanic share, at the national level, only for certain clusters of counties in the Southwestern and Western counties.

Zhu *et al*. (2021) also find that the epidemiological characteristics of the pandemic generated five main regional nodes, which are: New York, Chicago, Los Angeles, Miami, and Houston. These nodes concentrated the cases of Coronavirus and served as nodes to spread out the virus. They argue that these regional nodes formed for different economic, social, and environmental reasons.

Bossak and Andritsch (2022) argue that the spatial correlation between deaths and metropolitan areas is explained partially by the existence of a correlation between the pollution found at metropolitan areas and the severity of the disease.

1.4. Differences in economic and health outcomes between men and women

Several studies have documented differences in income levels between men and women in the US. Currently, the income gap between men and women stands at about 16% (Barroso and Brown, 2021), which means that despite public policies and other forms of inclusions women still earn on average only 84% of the income paid to men.

Similarly, scholars have consistently documented differences in the labor force participation rates between men and women. Since the 1970s, the rate of labor force participation for women has more than quadrupled, with 70% of women with children joining the labor force (Toosi, 2006). However, recent studies have shown that the labor force participation rate for women has stopped to grow and that for men has also declined. Despite these trends, the labor force participation of men remains about 10 percentage points above that of women (Bureau of Labor Statistics, 2007). In 2020, the participation rate of women was projected at 59.4% and is expected to decline to 55.1 % by 2050. Emerging research suggests that since the COVID-19 pandemic the labor force participation of women sharply declined, placing them at a greater economic disadvantage than those experienced in decades (Boulgaurt, 2020; Albanesi and Kim, 2021).

Not surprisingly, research has also documented differences between men and women in occupations, with sectors and industries showing differences in rates of female and male employment (Institute for Women’s Policy Research Institute, 2022). For example, for women, jobs in the health care, nongovernmental education, leisure, and other services account for more than 40% of women’s occupations, while the same sector account for only 25% of men’s occupations.

Differences in economic outcomes between men and women are linked to different factors, including labor market discrimination, productivity differences, as well as individual and group preferences (Azmat and Petrongolo, 2014), gender roles (Rice and Coates, 1995), and bargaining power in the labor market (Folbre, 2021).

Studies have documented differences in health outcomes between men and women, however, those differences also vary by country (Crimmins *et al.,* 2019). In terms of life expectancy, studies have found that men have a lower life expectancy than females (Barford *et al.,*

2006) in almost all countries. In the US, studies have found that this gender differential has in fact reduced, due to a reduction in the health advantage of women (Sasson, 2016).

In the case of the COVID-19 pandemic, studies have shown a higher death rate among males than females (Tokuyama and Mao, 2021). These differences have been linked to different biological responses by the immune system, as women's adaptive immune systems respond more to the disease while men's innate immune system responds more to the disease (Takahashi *et al.,* 2020), as well as to other biological factors (Tokuyama and Mao, 2021).

Another reason for differentiated health outcomes between men and women related to the pandemic, is the existence of differences in labor force participation rate, and occupations that exist between men and women. Men's labor force participation and occupations expose them differentially to the disease and to the public transportation as compared to women's labor force participation and occupations (Garcia *et al*., 2021). They also generate a differentiated access to health services (Garcia *et al*., 2021). For other authors, there exist also differences between men and women in rates of vaccination (Riley *et al*., 2021).

2. Empirical Methodology

In this paper, we combine two different empirical approaches to obtain an estimation of how COVID-19 affected income and employment in New York City. First, we follow the literature that measures changes in total output, by looking at how all inputs change (Young, 1995) expressed in equation (1):

$$\frac{\Delta Y_t}{Y_t} = \theta_{kt}\frac{\Delta K_t}{K_t} + \theta_{pt}\frac{\Delta P_t}{P_t} + PTFG_t \qquad (1)$$

Where the change in output is linked to the change in capital, the change in population and the change in total factor productivity. In this paper, we rewrite equation (1) as follows:

$$\Delta logInc_i = \beta_0 + Z_i^T \beta_1 + \gamma Nz_{i\neq j} + \lambda W \Delta logInc_{i\neq j} + \rho Mu_i + \epsilon_i \qquad (2)$$

Where $\Delta logInc$ represents the change in income measured between 2020 and 2019, at the level of the PUMA; Z_i is a vector of 15 control variables related to the change in inputs, $Z_{i\neq j}$ is the vector of the lags for the spatial correlation of the 15 control variables in PUMA j different from i, γ is a vector of parameters, N is a matrix of spatial correlations,λ is a vector of parameters, W is a matrix of spatial correlations, $\Delta logInc_{i\neq j}$ is the change in income in neighboring j pumas different to puma i, ρ is a vector of parameters, and M is a matrix of spatial correlations for the vector of errors u_i. Equation (2) attempts to estimate different sources of spatial correlation, related to the control variables, the endogenous variable, and the unobserved errors. Matrices N, W and M are specific to the spatial correlation patterns that emerge from control variables, contiguous values of the endogenous variable, and the unobserved effects. Their values are determined empirically as part of the estimation process. Control variables are measured at their 2019 level to avoid potential econometric problems, like reverse causality or endogeneity. They include human capital at the PUMA level, where human capital is measured by the share of population with some college or more education, proxies for investment and innovation measured by the shares of the population working in 13 occupation categories, and we also measure the 2019 total employment at the PUMA level. We include as control variable, the number of deaths that took place on average at the PUMA level for the period of November 2020 to June 2021. Using deaths as exogenous variable adapts the concept of the value of lost output (Alkire *et al.,* 2018), where instead of calibrating a model to obtain the effect of deaths on income, we simply use a reduced form approach to attempt to capture the correlation between observed deaths and changes in per capita income.

Finally, a third equation was estimated to obtain the impact of the deaths occurred in the analyzed period on the level of employment at the level of PUMA.

$$\Delta logEmp_i = \alpha_0 + X_i^T \alpha_1 + \pi Px_{i\neq j} + \varphi B \Delta logEmp_{j\neq i} + \mu Le_i \quad (3)$$

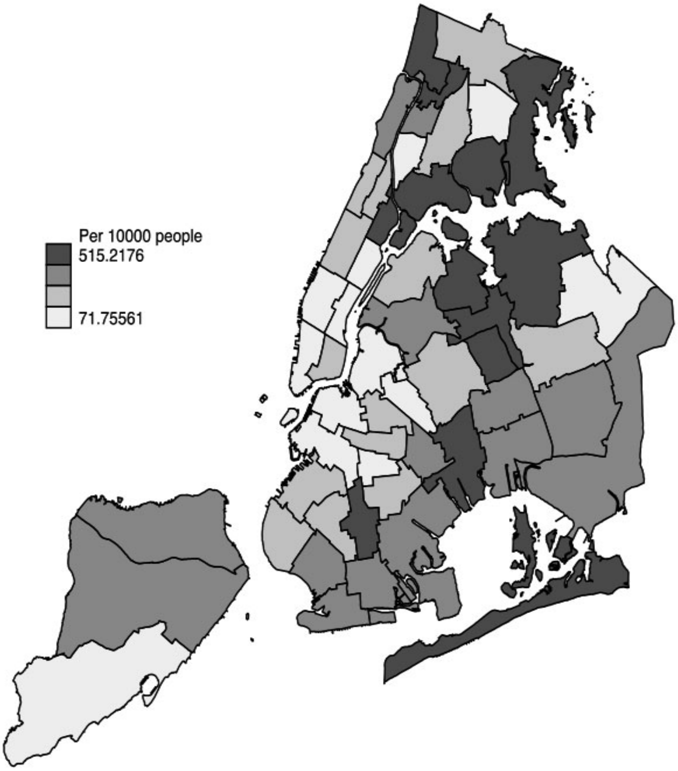
Where $\Delta logEmp$ represents the change in employment measured between 2020 and 2019, at the level of the PUMA; X_i is a vector of 15 control variables related to the change in inputs, π is a vector of parameters, P is a matrix of spatial correlations, $x_{i\neq j}$ is a vector for the lags of the spatial correlations for the 15 control variables in PUMA j different from i, φ is a vector of parameters, B is a matrix of spatial correlations, $\Delta logEmp_{j\neq i}$ is the change in employment in j pumas neighboring puma i, μ is a vector of parameters, and L is a matrix of spatial correlations for the vector of errors e_i. As before, equation (3) attempts to estimate the spatial correlation coefficients from the 15 control variables, the endogenous variable, and the unobserved errors. Matrices P, B and L are specific to the spatial correlation patterns that emerge from control variables, contiguous values of the endogenous variable, and the unobserved effects. Their values are determined empirically as part of the estimation process. Control variables are measured at their 2019 level to avoid potential econometric problems, like reverse causality or endogeneity. Control variables are like those described in equation (2), except because we exclude employment in 2019 and we include the log of the per capita income in 2019. The argument is that the level of per capita income represents how labor demand is linked to the level of income at the PUMA level.

Exploiting the spatial panel nature of the data has certain advantages over an OLS estimation. First, by considering the spatial correlation, we obtain a better estimation than the one offered by OLS. Second, the spatial specification allows to obtain direct and indirect effects due to the spatial correlation. Direct effects are those given by excluding the spatial correlation coefficients, while the indirect effects are those obtained when considering the different sources of spatial autocorrelation. The total effect is obtained by adding both direct and indirect effects. The estimation can be done by random or fixed effect estimations. This is decided empirically according to an application of a Hausman test proposed by Mutl and Pfaffermayr (2008).

3. Data Sources

Zip code data on mortality comes from NYC health which provides coronavirus cases and deaths by zip code (NYCH, 2022). The data was collected for the months of November 2020 through June 2021. Data was transformed to PUMA level using a cross walk of codes available from Baruch College Newman Library (Newman Library, 2022).

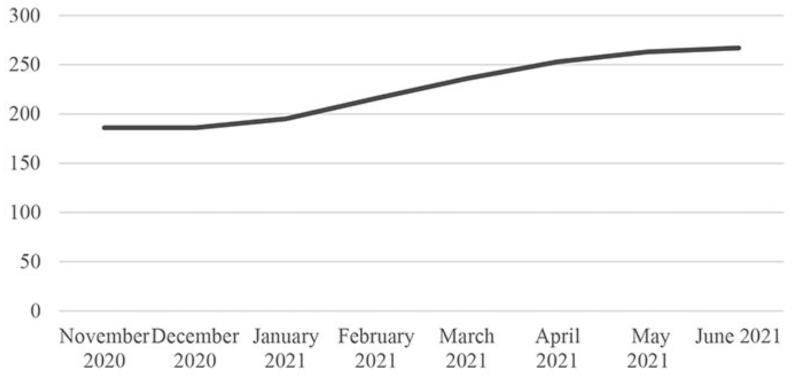
Figure 1
Mortality Rate



Source: own calculations with data from NYCH(2022).

As figure 1 shows, the average death rate by PUMA for the period of November 2020 to June 2021 does not show a uniform distribution, showing concentrations only for certain boroughs. The map shows the five boroughs of New York City which are: Bronx, Brooklyn, Manhattan, Staten Island and Queens. More deaths are observed in the Bronx and in Queens than in the other boroughs. Fuentes-Mayorga and Cuecuecha (2022) earlier work has shown that at the level of PUMA, there exists spatial correlation in the death rates for the Hispanic/Latino population in New York City. We confirm that result with this data.

Figure 2
Monthly Average Death Rate in New York City Pumas



Source: own calculations with data from NYCH (2022).

Figure 2 shows the average death rate per PUMA for the period beginning in November 2020 and ending in June 2021. It clearly shows a positive time pattern given the increase in the rate of deaths during the time.

The data for the PUMA characteristics was obtained from the 2019 American Community Survey 5 years public sample obtained from IPUMS (Ruggles *et al.,* 2022). Table 1 shows the average values for the different variables obtained from this source, for the entire sample, the men's sample, and the women's sample. For the entire sample, per-capita income increased 2.9%, while it increased 2.3% for men and 3.6% for women. Employment for the entire sample was 5483 persons per PUMA, while for the men's sample was 2796 and for the women's sample was 2687 individuals. The share with college stands out at 22% for the three samples. Per capita monthly income was 13 thousand dollars for the entire sample, 16 thousand dollars for the men's sample and 11 thousand dollars for the women's sample.

The fraction working in management for the entire sample was 11%, while for men it was 13% and for women it was 10%. The fraction working in computers was 3.9% for the entire sample, 5.9% for males and 2.2% for females. The share working in education is 11% for the entire sample, 9% for males and 12% for females. The fraction working

Table 1
Average values for variables used in this study (std. errors in brackets)

	All	Men	Women
Change in log pc income	2.90% [2.3%] 5483	2.30% [2.3%] 2796	3.60% [2.9%] 2687
Employment (number of indviduals)	[3203] 22.40%	[1713] 22.40%	[1497] 22.30%
Share with college	[7.3%] 13473	[7.4%] 16688	[7.2%] 11025
PC income (dollars)	[9891]	[12997]	[7856]
Management	11.80% [5.7%]	13.10% [6.6%]	10.70% [5.1%]
Computers	3.90% [1.6%]	5.90% [2.3%]	2.20% [1.1%]
Education	11.00% [3.9%]	9.00% [4.0%]	12.80% [3.9%]
Health	3.90% [1.2%]	2.30% [0.9%]	5.30% [1.6%]
Services	14.20% [4.2%]	12.90% [3.6%]	15.30% [4.9%]
Sales	7.00% [1.1%]	7.40% [1.5%]	6.60% [1.0%]
Office	8.70% [1.4%]	5.30% [0.9%]	11.60% [2.0%]
Farming	0.10% [0.1%]	0.20% [0.2%]	0.10% [0.1%]
Construction	2.80% [1.2%]	5.80% [2.4%]	0.20% [0.1%]
Installation	1.40% [0.6%]	2.90% [1.2%]	0.10% [0.1%]
Production	2.30% [1.1%]	3.20% [1.5%]	1.50% [0.8%]
Transportation	4.60% [1.7%]	8.20% [3.0%]	1.50% [0.7%]
Military	0.10% [0.4%]	0.20% [0.7%]	0.04% [0.1%]

Source: Own calculations with data from Ipums (Ruggles *et al*., 2022).

in health is 3% for the entire sample, 2% for males and 5% for females. The share working in services is 14% for the entire sample, while it is 12% for men and 15% for women. The share carrying out activities in sales is 7% for the entire sample, and it is also 7% for males and 6% for females. The fraction working in offices is 8% for the complete sample, it is 5% for males and 11% for females. The share working in farming is 0.1% for the entire sample and females, while it is 0.2% for males. The fraction working in construction is 2% in the complete sample, while it is 5% for males and 0.2% for females. The share working in installation is 1% for the entire sample, 2% for males and 0.1% for females. The fraction working in production is 2% for the complete sample, 3% for men and 1% for women. The share working in transportation is 4% for the entire sample, 8% for males and 1% for females. The fraction working in the military is 0.1% for the complete sample, it is 0.2% for men and 0.04% for women.

3.1. Random panel estimation for the 2020-2019 change in per capita income

Table 2 presents the estimated average impacts for the change in per capita income for the entire sample, the men's sample, and the women's sample. The data showed the importance of spatial autocorrelation for the three samples. A Hausman test shows that the differences between the random and fixed effect estimators is not systematic and consequently the random effect estimator is more efficient than the fixed effect estimator. [4]

The first three columns in table 2, show the direct, indirect, and total effects for the entire sample. The Pseudo R^2 for this model is 12%. The estimated total impact of deaths is a reduction of 0.61% in per capita income. The direct impact is found non-significant while the indirect impact is found to be a reduction of 0.71% in per capita income. These results show that the main reason for the reduction in per capita income is linked to the spatial correlation observed in the data, which can be claimed to show how the different factors leading to spatial stratification affects income in New York City. The estimated total impact for the share

[4] A calculated chi squared of 10.54 is obtained when applying the test suggested by Mutl and Pfaffermayr (2008), and it is smaller than a chi squared with K=18 degrees of freedom, which is 25.89 at the 10% degree of confidence and 34.805 at the 1% degree of confidence.

of population with college is found to be -0.43%. The indirect effect is -0.44% and the direct effect is non-significant. These results imply that the spatial concentration found among individuals with college education increased the negative impact of COVID-19 deaths on income. The total impact of the share of individuals in management is 0.27%, neither the direct nor the indirect effect alone are significant. These results imply that individuals in management occupations observed an increase in income due to COVID-19, probably reflecting a positive compensation paid to show up for work. The total impact of the share of individuals working in computer related jobs was 1.19%, while the direct and indirect effect are found insignificant. These results imply that individuals working with computers saw a productivity positive shock, as these occupations became more valuable during the COVID-19 pandemic. The total impact of individuals working in education occupations was 0.32%, with the direct effect being non-significant and the indirect effect being 0.51%. These results imply that for individuals working in education the spatial concentration produced positive effects on income. The total impact of the share of people working in health-related occupations is found non-significant, but the direct effect is found to be -1.05% and the indirect effect is found to be non-significant. These results imply that individuals working in health-related occupations saw a decrease in their income, which was offset by the spatial concentration. The effect for people working in office occupations the total effect is non-significant, while the direct effect is found to be 0.51%, but the effect is offset by the spatial correlation. This probably indicate that individuals working in office occupations could perhaps work from home, but such advantage may not have been available to all office employees. The total impact on farming occupations is found to be -11.02%, while the direct and indirect effect are not significant. These results reflect that occupations that had to shut down due to the confinement saw great declines. The total impact on construction is found to be 2.87%, while the direct effect is 2.48% and the indirect effect is non-significant. These results probably reflect the recovery in construction that occurred as part of the different economic policies implemented to counter act the negative effects of the pandemic. The total effect for occupations in installation is -2.57%, while the direct effect is -3.26% and the indirect effect is non-significant. These results imply that the pandemic reduced the business for installation occupations. No significant effects are found for occupations in services, sales, production, transportation, and the military. In total we observe 2 out of 13 cases where the spatial correlation was important and 3 out of 13 cases where the direct effects were important. In total we observe four sectors with positive shocks and two sectors with negative shocks.

Table 2
Estimated Average Impacts for Variables in the Income Equation

	All			Men			Women		
	Direct	**Indirect**	**Total**	**Direct**	**Indirect**	**Total**	**Direct**	**Indirect**	**Total**
Change in log deaths	0.11 [0.20]	-0.71** [0.32]	-0.60** [0.24]	0.26 [0.22]	-0.88** [0.44]	-0.62* [0.37]	-0.44 [0.27]	0.01 [0.50]	-0.43 [0.43]
Log of employment	0.02 [0.01]	-0.01 [0.01]	0 [0.01]	0.03*** [0.01]	-0.02 [0.02]	0.003 [0.02]	-0.001 [0.02]	0.004 [0.02]	0.003 [0.01]
Share with college	0.01 [0.18]	-0.44* [0.26]	-0.43*** [0.14]	0.18 [0.18]	-0.80** [0.38]	-0.63 [0.39]	0.01 [0.26]	0.17 [0.39]	0.18 [0.24]
Management	0.08 [0.26]	0.2 [0.33]	0.27* [0.15]	-0.51** [0.22]	0.78** [0.31]	0.27 [0.28]	0.5 [0.36]	-0.71 [0.53]	-0.21 [0.36]
Computers	0.34 [0.56]	0.85 [0.86]	1.19** [0.60]	-0.51 [0.43]	1.67** [0.67]	1.16 [0.71]	-1.3 [1.12]	-1.7 [1.82]	-3.00** [1.28]
Education	-0.19 [0.21]	0.51** [0.24]	0.32*** [0.10]	0.1 [0.18]	0.48 [0.29]	0.58*** [0.20]	-0.31 [0.24]	0.61** [0.31]	0.3 [0.18]
Health	-1.05*** [0.38]	0.96 [0.70]	-0.09 [0.45]	-0.65 [0.44]	0.43 [0.79]	-0.22 [0.67]	-1.15** [0.46]	0.74 [0.85]	-0.41 [0.55]
Services	-0.08 [0.19]	0.35 [0.26]	0.28 [0.19]	-0.25 [0.23]	0.59 [0.40]	0.34 [0.47]	-0.34 [0.23]	0.08 [0.31]	-0.25 [0.18]
Sales	0.26 [0.52]	-0.35 [0.73]	-0.09 [0.44]	0.63 [0.39]	-0.51 [0.65]	0.11 [0.62]	-1.74** [0.70]	1.25 [1.08]	-0.49 [0.65]
Office	0.51* [0.30]	-0.57 [0.56]	-0.06 [0.49]	0.26 [0.49]	0.57 [1.08]	0.83 [1.06]	0.1 [0.33]	-0.31 [0.45]	-0.21 [0.37]
Farming	-2.83 [4.55]	-8.18 [5.89]	-11.02*** [4.02]	1.19 [2.87]	-4.73 [5.44]	-3.54 [6.14]	-10.87 [8.65]	-5.76 [11.08]	-16.63** [7.06]
Construction	0.39 [0.52]	2.48*** [0.65]	2.87*** [0.60]	0.16 [0.26]	1.09** [0.46]	1.25** [0.50]	1.11 [6.51]	3.84 [8.60]	4.96 [7.49]
Installation	-3.26*** [1.05]	0.68 [1.33]	-2.57*** [0.65]	-1.35** [0.55]	-0.16 [0.85]	-1.51** [0.68]	-3.77 [6.61]	41.11*** [10.05]	37.34*** [10.49]
Production	0.15 [0.63]	0.18 [0.81]	0.34 [0.46]	-0.51 [0.47]	0.19 [0.76]	-0.32 [0.76]	2.36** [0.97]	1.53 [1.45]	3.89*** [1.17]
Transportation	0.18 [0.42]	-0.43 [0.55]	-0.25 [0.37]	0.18 [0.25]	-0.3 [0.38]	-0.12 [0.33]	-0.89 [1.18]	-2.74 [2.35]	-3.62* [2.05]

Table 2 (Continuation)

Estimated Average Impacts for Variables in the Income Equation

	All			Men			Women		
	Direct	**Indirect**	**Total**	**Direct**	**Indirect**	**Total**	**Direct**	**Indirect**	**Total**
Military	0.5 [0.80]	-1.57 [1.05]	-1.07 [0.88]	-0.57 [0.47]	1.67** [0.76]	1.1 [0.69]	5.37 [3.91]	-2.59 [5.87]	2.78 [5.24]
N		236			236			236	
Pseudo R^2		12%			15%			9%	

Source: own calculations with data from IPUMS (Ruggles *et al.*, 2022).
*1 % significance; **5 % significance; *** 10% significance

In the case of the men's sample, the results are shown in columns 4, 5 and 6 of table 2. The Pseudo R^2 is 15% for this sample. The total effect of deaths in income is a reduction of 0.62%. The direct effect is found non-significant, while the indirect effect is -0.88%. This suggests that almost the entire impact observed in the whole sample is explained for what happened to men, and particularly to the spatial concentration. The total impact for the log of employment is found to be non-significant, while the direct effect is 0.03% and the indirect effect is non-significant. These results imply that the increase in employment for men pushed incomes up, but this effect was counteracted by the effects of the spatial concentration. The total effect for the fraction with college is non-significant, while the indirect effect is -0.8% and the direct effect is non-significant. These results imply that the spatial concentration reduced incomes of the college educated. The total impact for management occupations is non-significant, while the direct effect is -0.51% and the indirect effect is 0.78%. These results contrast with those found for the entire sample where a positive total impact was found. The total impact for occupations with computers is non-significant, while the indirect effect is 1.67% and the direct effect is non-significant. These results imply that the spatial correlation affected positively the income of these occupations. The total impact for occupations in education is 0.58%, while the direct and indirect effect is non-significant. These results imply the existence of a positive shock for this type of occupations. The total impact for construction workers is 1.25%, while the indirect effect is 1.09% and the direct effect is non-significant. These results confirm what was found in the entire sample. The total impact of installation occupations is -1.51%, while the direct effect is -1.35% and the indirect effect is non-significant. This result also confirms what was found in the entire sample. The total effect for the occupations in the military was non-significant, while indirect effect is 1.67% and the direct effect is non-significant. These results imply that the spatial correlation helped these occupations. No significant effects are found in occupations in services, sales, office, farming, production, and transportation.

In the case of the women's sample, columns 7, 8 and 9 of table 2 present the results. The Pseudo R^2 is 9% for this sample. The total effect for the change in deaths is found non-significant, as well as the direct and indirect effects. This would indicate that policies that were implemented in New York City benefited more women relative to men, which may be explained by the sectors in which women specialize (Albanesi, 2020). The total effect for occupations in computers is found to be -3%, while the indirect and direct effect are non-significant. This results probably reveals that women had to give up their incomes to maintain this type of occupations. The total effect for occupations in educations is non-significant, while the indirect effect is 0.61% and the direct effect is non-significant. These results shows that occupations in education benefited from the spatial correlation. The total impact for occupations in health is non-significant, while the direct impact is -1.15% and the indirect effect is non-significant. This result show that occupations in health services saw a decline in their income. The total impact on sales occupations is non-significant, while the direct effect is -1.74%, and the indirect effect is non-significant. These results imply that occupations in sales saw a decline in productivity. The total impact on farming occupations is -16.63%, while the direct and indirect effects are not significant. These results confirm what was found in the entire sample. The total impact on installation occupations is 37.34%, while the indirect effect is 41.11% and the indirect effect is non-significant. These results contrast with those found for the entire sample, which probably show that there was a shift between men and women during the pandemic. The total impact on occupations in production is 3.89%, while the direct impact is 2.36% and the indirect effect is non-significant. These results imply a positive productivity shock in production for women. The total impact for transportation is -3.62%, while the direct and indirect effect are non-significant. These results imply the existence of a negative shock in transportation occupations for women. No significant effects are found for occupations in management, services, office, construction, and the military.

In short, deaths caused by the pandemic had different impact on the economic life chances of men and women in New York City, probably due to the different sectors in which both gender groups concentrated, including the different responses to the pandemic taken by the two gender groups and the economic measures taken by the authorities of New York City which varied by sectors and individuals. For men, two out of thirteen sectors showed direct effects, three out of thirteen sectors showed indirect effects; while for women, these numbers are exactly the opposite three out of thirteen sectors saw direct effects and two out of thirteen sectors saw indirect effects. We can conclude that the importance of the spatial correlation is similar for men and women. In the case of total effects, for men, three sectors showed positive effects and two sectors showed negative effects, while for women, two sectors showed positive effects and three sectors showed negative effects. This indicates that the pandemic generated more sectors with negative effects among women than among men, even though the aggregated effect on women is zero, while it is negative for men. This may indicate that women did not accept wage declines and potentially quit their jobs. These clearly indicates that innovation and adaptability by sectors was heterogenous over the pandemic, with some sectors adapting better to the circumstances. Interestingly, the adaptability is linked to the gender of the individuals as exemplified by the occupations in installation services where a negative productivity shock is observed among men, while a positive shock is observed among women.

3.2. Random panel estimation for the 2020-2019 change in employment

Table 3 presents results for the impact of deaths on the employment for the entire sample, the men's sample, and the women's sample. The data also showed the presence of spatial autocorrelation in the three samples analyzed. As in the case of the estimations for income, a Hausman test shows that the differences between the random and fixed effect estimators is not systematic and consequently the random effect estimator is more efficient than the fixed effect estimator.[5]

In the case of the whole sample, columns 1, 2 and 3 in table 3 show the results. The Pseudo R^2 for this model is 5%. The total effect of the number of deaths is to increase employment in 0.25%, while the direct and indirect effect are non-significant. This result seems paradoxical, but it is important to remember that it looks at what happened during the November 2020 and June 2021 period, and consequently the data already captures economic recovery as indicated by the data[6]. Moreover, the increase in employment is consistent with our results, one that finds a decline in per capita income, since it reflects that on average, wages declined, and employment increased. The total effect of the income per capita is to increase employment 0.03%, while the direct effect is 0.06% and the indirect effect is non-significant. These results imply that the economic stimulus influenced positively employment. The total effect of the occupations in management is -0.92%, while the direct effect is -1.31% and the indirect effect is non-significant. This imply that impact of the COVID-19 shock was to reduce employment in management occupations. The total employment in health occupations was -0.37%, while the direct and indirect effects are non-significant. This result implies that jobs in health services reduced during the pandemic. The effect on services is -0.61%, the indirect effect is -0.93% and the direct effect is non-significant. These results imply that a reduction in services occupations occurred due to the spatial correlation. The total effect on sales occupations is 0.60%, while the indirect effect is 1.86% and the direct effect is non-significant. This implies that occupations in sales increased due to the spatial correlation, probably showing increases in delivery services. The effect on office occupations is 0.52%, while the direct and indirect effect is non-significant. These jobs probably could be performed remotely, and this explains its increase. Jobs in farming has an effect of -5.95%, the indirect effect is -13.70% and the direct effect is non-significant. This result imply that this type of jobs was affected by the spatial correlation. The effect on construction jobs

[5] A calculated chi squared of 18.04 is obtained when applying the test suggested by Mutl and Pfaffermayr (2008), and it is smaller than a chi squared with K=18 degrees of freedom, which is 25.89 at the 10% degree of confidence and 34.805 at the 1% degree of confidence.

[6] Data from labor statistics shows an increase in employment for the period analyzed (see https://dol.ny.gov/labor-statistics-new-york-city-region).

was -2.60%, the indirect effect is -3.55% and the indirect effect is non-significant. Construction jobs were also affected by the spatial correlation. Jobs in installation occupations reduced 0.80%, while the direct and indirect effect were non-significant. This implies that a negative shock existed on installation occupations. Jobs in production occupations increased 2.20%, the indirect effect is 3.3% and the direct effect is non-significant. The spatial correlation benefited jobs in production. Jobs in the military saw an increase of 1.85%, the direct and indirect effect were non-significant. It is important to mention that for the effect on employment, the spatial correlation effects were significant in 5 out of 13 sectors, while the direct effects were important in 1 out of 13 sectors, while we observe five out of 13 sectors with negative shocks and 4 out of 13 sectors with positive shocks.

Table 3
Estimations for the average impact for employment

	All			Men			Women		
	Direct	**Indirect**	**Total**	**Direct**	**Indirect**	**Total**	**Direct**	**Indirect**	**Total**
Change in log deaths	-0.29 [0.33]	0.55 [0.37]	0.25* [0.14]	-0.04 [0.14]	0.63** [0.29]	0.59** [0.25]	-0.15 [0.14]	0.29 [0.36]	0.14 [0.35]
Log of pc income	0.06* [0.04]	-0.03 [0.03]	0.03*** [0.01]	0.05** [0.02]	-0.01 [0.02]	0.04** [0.01]	0.02 [0.02]	-0.02* [0.01]	0.01 [0.01]
Share with college	0.67 [0.49]	-0.68 [0.48]	-0.01 [0.05]	0.19 [0.13]	-0.07 [0.17]	0.12 [0.14]	0.18 [0.12]	0.25 [0.26]	0.43** [0.19]
Management	-1.31** [0.59]	0.39 [0.63]	-0.92*** [0.16]	-0.68*** [0.24]	-0.19 [0.30]	-0.86*** [0.20]	-0.45** [0.19]	-0.87** [0.43]	-1.31*** [0.40]
Computers	0.11 [0.54]	0.01 [0.73]	0.13 [0.37]	0.13 [0.26]	0.17 [0.33]	0.29 [0.28]	0.05 [0.53]	3.14** [1.08]	3.19*** [1.02]
Education	0.02 [0.21]	0.01 [0.23]	0.03 [0.05]	-0.01 [0.13]	-0.05 [0.20]	-0.06 [0.11]	-0.26** [0.13]	0.18 [0.19]	-0.08 [0.12]
Health	0.26 [0.37]	-0.63 [0.43]	-0.37* [0.20]	0.71** [0.31]	-0.49 [0.54]	0.21 [0.48]	0.12 [0.22]	-0.52 [0.38]	-0.4 [0.38]
Services	0.32 [0.47]	-0.93** [0.46]	-0.61*** [0.11]	0.02 [0.13]	-0.3 [0.23]	-0.27 [0.21]	-0.1 [0.12]	-0.23 [0.16]	-0.33** [0.14]
Sales	-1.26 [1.14]	1.86* [1.13]	0.60* [0.32]	-0.38 [0.25]	0.15 [0.42]	-0.23 [0.42]	-0.22 [0.38]	1.06** [0.53]	0.84** [0.39]
Office	0.4 [0.31]	0.13 [0.49]	0.52** [0.26]	0.75** [0.35]	-0.63 [0.71]	0.12 [0.52]	-0.08 [0.15]	0.34 [0.24]	0.26 [0.25]
Farming	7.76 [8.11]	-13.70* [8.26]	-5.95* [3.35]	-2.07 [1.72]	-1.77 [3.33]	-3.83 [3.39]	0.66 [4.38]	-8.18 [5.88]	-7.52* [4.48]
Construction	0.95 [1.79]	-3.55** [1.63]	-2.60*** [0.41]	-0.16 [0.23]	-1.24*** [0.26]	-1.40*** [0.35]	-3.88 [3.68]	-15.69*** [5.38]	-19.57*** [6.88]
Installation	-0.17 [1.04]	-0.63 [1.21]	-0.80*** [0.34]	0.11 [0.40]	-0.86 [0.63]	-0.75** [0.37]	-0.38 [3.33]	-14.07*** [5.45]	-14.45*** [5.51]

Table 3 (Continuation)
Estimations for the average impact for employment

	All			Men			Women		
	Direct	**Indirect**	**Total**	**Direct**	**Indirect**	**Total**	**Direct**	**Indirect**	**Total**
Production	-1.1 [1.71]	3.31** [1.58]	2.20*** [0.38]	0.16 [0.34]	2.11*** [0.49]	2.28*** [0.49]	0.08 [0.53]	-0.88 [0.88]	-0.8 [0.77]
Transportation	0.42 [0.51]	-0.47 [0.54]	-0.05 [0.21]	0.17 [0.18]	-0.34 [0.22]	-0.17 [0.17]	0.38 [0.62]	3.35** [1.65]	3.72** [1.75]
Military	-1.18 [1.91]	3.03 [1.98]	1.85*** [0.54]	0.28 [0.31]	0.88* [0.52]	1.16** [0.48]	0.19 [1.69]	-4.64 [3.60]	-4.45 [3.42]
N		236			236			236	
Pseudo R^2		5%			8%			4.30%	

Source: own calculations with data from IPUMS (Ruggles *et al.,* 2022). * 1% Significance. ** 5% Significance. *** 10% Significance.

In the case of the men's sample, columns 4, 5 and 6 in table 3 present the results. The Pseudo R^2 for this sample is 8%. The total impact of deaths is an increase of 0.59% in the number of employed individuals. The indirect effect is 0.63% and the direct effect is non-significant. This result is consistent with the observed decline in per capita income among males, since it implies that on average wages were reduced for males, while employment increased. This also shows that the results observed reflect choices and not only availability of economic or social programs by New York City. The total effect of income is 0.04%, the direct effect is 0.03% and the indirect effect is non-significant. These results mark the importance of the economic stimulus for the creation of employment. The total effect for the occupations in management is -0.86%, while the direct effect is -0.68% and the indirect effect is non-significant. This result probably reflects the disappearance of many small business. The total effect on education is -0.26%, while the direct and indirect effect are insignificant. This probably shows the shutdown of schools. The effect on construction occupations is -1.4%, the indirect effect is -1.24% while the direct effect is non-significant. This shows that the spatial correlation affected construction jobs. The total effect on installation occupations is -0.75%, while the direct and indirect effect is non-significant. This result also shows the effects of the shutdown. The total effect in production is 2.28%, while the indirect effect is 2.11%. These results probably indicate the effect of the economic stimulus in the economy. The total effect for the military is 1.16%, while the indirect effect is 0.88%. This probably shows that occupations in the military work as employer of last resort.

In the case of the women's sample, columns 7, 8 and 9 of table 3 show the results. The Pseudo R^2 for this sample is 4.3%. The total effect of deaths on employment is non-significant, as well as the direct and indirect effect. This result is consistent with finding that no reduction in per capita income was observed among females, and consequently no reduction in wages occurred. This result may suggest that as women suffered the greatest job losses, especially as the majority concentrates in service sectors, they did may have been the gender group to benefit most from the social 'safety-net' programs offered by the City of New York and the Federal government to stimulate the economy. The total effect of per capita income is non-significant, while the indirect effect is -0.02%, showing that the spatial concentration affected the employment of women. The total effect of college educated individuals is to increase employment 0.43%. The direct and indirect effect are non-significant. This shows that college education helped women to stay employed. The total effect in management occupations is -1.31%, with direct effect being -0.45% and the indirect effect being -0.87%. These results probably reflect the disappearance of many small business. The total effect on occupations related to computers is an increase of 3.19%. The indirect effect is 3.14%, while the direct effect is non-significant. These results imply that occupations in the computer industry benefitted women. The effect in services occupations is -0.33%, with the direct and indirect effect non-significant. This result probably shows the effects of the shutdown. The total effect on sales occupations is an increase in 0.84%, with the direct effect being non-significant and the indirect effect being 1.06%. This result may show that occupations for women shifted to sales as a strategy to generate income after the pandemic. The total effect on occupations related to farming is -7.52%, with direct and indirect effect being non-significant. This probably shows the effect of the shutdown. The total effect for occupations in construction was a decline of -19.57%. The indirect effect is -15.69%, while the direct effect is non-significant. These results show that construction jobs were specially hit by the spatial correlation. The total effect on transportation occupations is 3.72%, the indirect effect is 3.35%, while the direct effect is non-significant. These results probably show that transportation was an essential sector.

Our results show that the effects on employment differed between men and women. For men, three sectors showed direct effects and three sectors showed indirect effects; for women, two sectors showed direct effects and six sectors showed indirect effects. This signals out that women were more affected by the spatial correlation effects if measured by the number of sectors affected by the indirect effects. Our results also show that for men two sectors experienced positive shocks and three sectors experienced negative shocks; while for women, five sectors showed negative impacts and three sectors showed positive impacts. These results signal out that women experienced more sectors with negative impacts than men, even if on average deaths did not generate changes in employment among women. These results indicate that among women, more job reallocations took place, the exact nature of such job reallocations cannot be determined with the data at hand.

In the case of men, if we take these results together with our previous result of a decline in wage income, men accepted wage declines and that when recovery occurred, more men found jobs, while income from wages continued to not recover.

In the case of women, when we analyze these results together with our previous finding about the fact that income did not decline for women, it may be the case that women chose to quit their jobs, instead of taking a reduction in wages, or that family obligations, as decades of research have shown (Albanesi, 2020) forced women to quit their jobs, given their over concentration in services that require high level of interaction with those they service, such as in the schools, hospitality, and home-attendant and domestic care sectors. Once the recovery took place, the labor market returned to its previous employment level, not showing changes in employment or income for women.

However, our findings suggest that this effect took place with important reallocations between sectors, since for women more sectors showed more negative shocks compared to men, so it looks like women changed jobs and sectors without accepting wage declines and consequently the net labor demand for women did not change.

Our results cannot rule out the possibility that women experienced labor market discrimination during the pandemic, as many of the jobs where they have traditionally concentrated had the highest levels of COVID-19 exposure and also because many of their service jobs did not offer them the flexibility to work from home or long distance, given the different constraints imposed on them by family and new household burden during a health pandemic.

Conclusions

This paper studies the relation between deaths due to COVID-19 during the period of November 2020 to June 2021 at the PUMA level and the changes in average PUMA per capita income and PUMA level of employment. The results demonstrate the existence of spatial correlation in the data and their importance in understanding the total effect of the pandemic. In particular, we found that spatial correlation was important for two sectors in terms of wage income and it was important for five sectors in terms of employment. Moreover, the results show that a one percent increase in deaths reduced per capita income 0.60% and that increased 0.25% employment. Similarly, our analysis shows that there were important differences between sectors, since the data shows six out of thirteen sectors with reductions in employment, while only four sectors showed increases in employment during this period.

The analysis was carried out for men and women separately. The analysis for men demonstrates that a one percent increase in deaths increases income 0.62 percent while increased employment 0.59%. In the case of women, no effects are observed for either income or employment. The results, however, are different when the analysis is carried out per sector.

Spatial correlations are found to be important both for men and women in this analysis by sector. In the case of the effect on income the results of spatial correlation are similar between men and women, as the results show that the impact of spatial correlation was observed in three sectors out of thirteen in the case of men and two sectors out of thirteen for women. In the case of the effect on employment the results of spatial correlation are more negative for women than for men, as the results show that three sectors had indirect effects for men and six sectors had indirect effects for women.

The total effect also differed between men and women. In the case of income, for men, positive effects are found in three sectors and negative effects are found in one sector; while for women, positive effects are found in two sectors and negative effects in three sectors. These results imply worst results for women by sector. In the case of employment, for men, three sectors show negative effects while two sectors experience positive effects; while for women, three sectors show positive effects, and five sectors show negative effects. Once again, women are more affected by sector.

These results show that policies implemented in New York City in response to the economic contraction observed during the COVID-19 pandemic worked differentially for men and women. These results also show that men and women responded differentially in their labor market choices. It is shown that on average men accepted reductions in their wages, which increased their employment, while women did not experience changes in income or employment.

Moreover, the results show that the reductions in employment were also different for men and women by sector, since for women five out of thirteen showed reductions in employment while for men only three sectors showed reductions in employment. Whether these results reflect an interaction between policies and choices taken by men and women, or the existence of labor market discrimination against women cannot be distinguished with the data at hand.

Further in deep analysis is needed to better understand how labor markets interacted with policies and choices of men and women during the pandemic, and if there is evidence that the labor market practices discrimination against women during economic shocks.

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