Public Transit and Air Pollution^{*}

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Abstract

Advocates of public transit frequently tout improved air quality as a primary benefit. Yet little is known about the causal impacts of public transit on local air pollution. Exploiting variation in transit availability resulting from work stoppages in 18 Canadian cities between 1974–2011, this study identifies the effect of public transit on air pollution. Our findings indicate that transit leads to a 3.5 part-per-billion increase in nitrogen oxides while having no statistically significant effect on carbon monoxide or $PM_{2.5}$. Estimates are robust to a series of specification and placebo tests and magnitudes are consistent with a calibrated simulation model. Overall, the results suggest that expanding the current configuration of public transit in North American cities is unlikely to yield improvements in local air quality.

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1 Introduction

Traffic-related air pollution leads to adverse health outcomes,¹ deteriorated cognitive performance² and reduced labor productivity.³ Curbing vehicular emissions has, as a result, become a central goal of environmental policy with investment in public transit emerging as a broadly endorsed strategy for improving traffic-related air quality (Beaudoin, Farzin and Lawell, 2015).⁴ Yet, it is unclear whether expanded public transit actually decreases local pollution. Like other light-duty vehicles, buses burn fossil fuels and trains require electricity whose generation may originate from high-emission sources. Advocates implicitly assume that enhanced public transit will motivate a sufficiently large number of commuters to substitute from cars to buses and trains, ultimately improving air quality. The fundamental law of road congestion, however, contends that expanding public transit will have little effect on the number of vehicle kilometres traveled by cars (Downs, 1962; Duranton and Turner, 2011): improved transit may induce some commuters to substitute from cars to buses or trains, but a large latent group of drivers will quickly occupy the freed capacity.

This paper estimates the causal relationship between the provision of publicly provided transit and air pollution. Using daily and hourly pollution data, we exploit as-good-asrandomly assigned transit union strikes in 18 Canadian cities. Across the entire sample, we show that transit work stoppages lead to a large and statistically significant decrease in atmospheric nitrogen oxide (NO_X) concentrations equal to 3.5 parts per billion (ppb). Transit strikes also result in an imprecisely estimated, statistically insignificant increase in carbon monoxide (CO) and a small and statistically insignificant decrease in PM_{2.5} concentrations. Investment in public transit therefore entails more NO_X pollution while having little meaningful effect on other pollutants. Thus, the prospect for an environmentally advantageous pollution swap, where pollution generated by private vehicles is swapped for emissions from

¹A range of literature explores the link between traffic-related air pollution and health – see, for example, (e.g., Currie and Neidell, 2005; Chay and Greenstone, 2003; Künzli et al., 2000; Krämer et al., 2000; Currie et al., 2009; Neidell, 2009; Xia et al., 2015; Jerrett et al., 2014).

²Lavy, Ebenstein and Roth (2014), for instance, shows that exposure to carbon monoxide and $PM_{2.5}$ lead to lower test scores for college entrance exams in Israel, while Bharadwaj et al. (2017) find that fetal pollution exposure leads to lower fourth grade test scores in Santiago, Chile.

³Chang et al. (2016) and Zivin and Neidell (2012), for example, illustrate that exposure to ozone reduces the productivity of agricultural workers in California.

⁴For example, environmental groups in the city of Toronto have endorsed transit's air-quality benefits, stating that without further public transit investment, "Toronto's air would be significantly dirtier and we would be emitting hundreds of thousands of tonnes of additional greenhouse gas (ghg) emissions into the atmosphere" (Toronto Environmental Alliance, 2010). Likewise, in December 2016, the city of Paris made public transportation free to riders in an effort to combat severe air pollution (Sharman, 2016).

public transit leading to an overall improvement in air quality, is limited. Rather, increasing the number of buses on the road deteriorates a city's overall air quality. A stylized analytical model, calibrated to match Canadian commuting behavior (the setting for the empirical component of the paper), supports the econometric results: it is likely that public transit in North America results in increased NO_X emissions. On average, the current configuration of public transit in North American cities does not improve local air quality.

A burgeoning literature links public transit to pollution.⁵ Friedman et al. (2001) investigate the impacts of a city-wide change in transport infrastructure, including increased public transit provision and severe downtown driving restrictions that were put in place during the 1996 Summer Olympic Games in Atlanta, and find that pollution monitors in downtown Atlanta recorded a 27.9% decrease in peak daily ozone concentrations. Chen and Whalley (2012) find that the opening of Metropolitan Rapid System in Taipei reduced carbon monoxide (CO) concentrations by 9 to 14% (while having no impact on other pollutants), while Lalive, Luechinger and Schmutzler (2013) show that increasing the frequency of rail services in Germany is associated with lower concentrations of CO and NO_X . Bel, Holst et al. (2015) find that Mexico City's "Bus Rapid Transit" system is effective at reducing NO_X, CO and $PM_{2.5}$. At the global scale, Gendron-Carrier et al. (2017) use satellite imaging and a panel of international subways expansions to demonstrate a 4% reduction in airborne particulates.⁶ In contrast, in an international panel of 75 cities, Hilber and Palmer (2014) highlight that, as the number of cars increases, annual NO_X concentrations decrease. Likewise, using data from a panel of 96 US cities, Beaudoin and Lin Lawell (2016) find that increases in the provision of public transit result in a small deterioration in urban air quality. Much of this research however focuses on isolated geographical locations, potentially limiting the generalizability, or uses annual data, making identification of the impact of public transport difficult.

This paper's conclusions run counter to much of the existing literature on public transport and air quality. Rather than improving air quality, we demonstrate that public transit increases local pollution levels (in particular, NO_X concentrations). We posit two likely reasons for these differences. First, we examine a panel of North American cities. Compared

⁵A broader literature connects public transit to traffic congestion – for example, Anderson (2014); Winston and Maheshri (2007); Aftabuzzaman, Currie and Sarvi (2010). Likewise, several recent studies link traffic congestion to different health outcomes (Levy, Buonocore and Von Stackelberg, 2010; Knittel, Miller and Sanders, 2011; Currie and Walker, 2011).

⁶However, it is worth noting that Gendron-Carrier et al. (2017) regard the 4% estimate as too large to be plausible, given current technologies.

to Asia or Europe, North America has unique traffic patterns, geography and economic structure. These structural factors are likely the major basis for the discrepancies. Indeed, Beaudoin and Lin Lawell (2016) who also study public transit in North American cities, finds conclusions that are aligned with ours. Second, while much of the literature focuses on the impact of new subway lines on air pollution (Gendron-Carrier et al., 2017; Chen and Whalley, 2012; Lalive, Luechinger and Schmutzler, 2013), we focus instead on existing public transport systems in North America, which are dominated by buses. Buses typically burn diesel, while subways use electricity. Hence, different patterns of results are expected.

Methodologically, the paper most similar to ours is Bauernschuster, Hener and Rainer (2017).⁷ Bauernschuster, Hener and Rainer (2017) show that a public transit strike is accompanied by a 14% *increase* in particulate pollution (PM_{10}) in the five largest German cities. Like us, they use work actions for econometric identification. Yet, despite the outward similarity of the two papers, the contexts and implications are quite different. First, Bauernschuster, Hener and Rainer (2017) examine extremely short work stoppages. All of the strikes in their data span less than 24 hours, with many as brief as two hours or less. Strikes in our analysis are longer, lasting several weeks on average. This means that the two papers are estimating fundamentally different parameters: while it is reasonable to delay commuting in response to a very brief strikes such as those in Bauernschuster, Hener and Rainer (2017), such avoidance behaviour is much more challenging for strikes that last several weeks. Further, as mentioned, caution should be exercised when generalizing from large German metropolises to the North American context as the configuration of cities, baseline levels of pollution, economic structure and travel mode shares are different. For example, while diesel passenger vehicles are common in European countries, they represent a tiny niche in North America. Gasoline and diesel vehicles emit distinct pollutant mixes, so this implies that transit displaces different pollutants on the two continents. Moreover, given that our conclusions are very different than those of Bauernschuster, Hener and Rainer (2017) (and several of the other papers), this suggests that a consensus on the relationship between public transit and air quality is likely context-specific and that additional research on the topic is warranted.

Identifying the causal effect of public transit on air pollution is challenging for three reasons. First, the supply of public transit is not randomly assigned and is generally confounded

⁷Our paper is also similar to Anderson (2014), who identifies the effect of public transit using public transit strikes. Anderson (2014) uses the LA transit strike of 2003 to measure the impact of transit on congestion, whereas we focus on air quality.

with other factors that influence air quality (Chen and Whalley, 2012; Beaudoin, Farzin and Lin, 2014). The supply of buses, for instance, tends to be greater in cities where the congestion is also high. This prototypical endogeneity problem explains the focus on short-run changes in air quality: parameter identification at these time scales is more clearcut. Second, the impacts of public transit on air quality depend on the ability and willingness of commuters to substitute between modes of transportation. Obtaining reliable, high frequency data on private and public transit usage has proved challenging. Without these data, it is difficult to eliminate plausible alternative explanations for regression results. Limited data also prevents credible estimation of important structural elasticities. Third, variation in the demand for public transit is confounded with other covariates which influence air quality. Anderson (2014), for example, demonstrates that mode demand is time-varying. Demand for public transit is higher during rush hours when pollutant concentrations are also elevated. City-specific economic conditions likewise lead to greater demand for buses and more emissions from industrial production. Ignoring the potential endogeneity of public transit investment can lead to large variation in policy-relevant parameters. Beaudoin, Farzin and Lawell (2015), for example, show up to a 40% understatement of the benefits from transit in a regression of air pollution on transit. We avoid many of these problems by combining high frequency data with good-as-random variation in transit availability. While our results focus on the short-run response to changes in transit availability, we believe that our compelling identification strategy along with high resolution data make this paper a valuable contribution to the existing body of research in this area. Moreover, we view our paper as providing evidence on the impact of transit on pollution in North America, a region with few existing studies.

The remainder of the paper contains four sections. Section 2 presents a stylized model that outlines the scope for an environmentally beneficial pollution swap as envisioned by public transit advocates. Section 3 describes our primary econometric model including our identification strategy and data. Section 4 presents our results. This section includes several robustness checks and an investigation of intra-day heterogeneity. Section 5 concludes.

2 Scope for a Pollution Swap

Research demonstrating how public transit improves air quality implicitly makes assumptions about commuters' willingness to substitute between traveling and other goods and, more importantly, their willingness to substitute between taking transit and using private vehicles. Improved air quality from expanded transit systems depends on the prospect of a pollution swap whereby pollution from cars is swapped for (hopefully less) pollution from public transit vehicles. The potential for this substitution, of course, depends on commuters' responsiveness to changes in key attributes of transit such as its availability, quality and price. Section 3 uses reduced form econometric models to estimate the effect of public transit on air quality, but we begin by presenting a stylized model that outlines the mechanism through which public transit affects air quality. Parameterizing this model using plausible values for Canada, we illustrate that investments in public transit can indeed improve air quality, yet the scope for an environmentally beneficial pollution swap is limited. Our later empirical results further demonstrate that the necessary substitutions between public transit and private vehicles do not appear to be observed in our data.

2.1 Analytical Model

Aggregate vehicular emissions depend on both technological and behavioral factors. Characteristics such as vehicle age, vehicle size, trip frequency and average speed influence overall emission rates. Fuel-type, in particular, has a central role in the level of different types emissions. Panel A of Table 1 shows the per mile emission rates for NO_X, CO, and PM_{2.5}, from a model year 2010 diesel fueled bus and gasoline fueled car, based on estimates from Cai, Burnham and Wang (2013).^{8,9} Per mile traveled, buses emit 1.3 grams of NO_X, 1.1 grams of CO, and 22 milligrams of PM_{2.5}. Cars, in contrast, emit substantially less NO_X at 0.1 grams per mile, three times as much CO at 2.9 grams per mile, and three times less PM_{2.5} at 7 milligrams per mile.^{10,11}

⁸In North America, buses typically use diesel, while private vehicles burn gasoline. Emissions per mile are estimates for mileage-weighted lifetime emissions for each vehicle.

⁹We concentrate on three main "criteria" pollutants that are released by vehicles: NO_X , CO, and $PM_{2.5}$ (note that $PM_{2.5}$ is both released directly by vehicles as well as formed indirectly in secondary reactions). The choice of pollutants is motivated by data availability; however, cars and buses have differential emission rates for other pollutants as well. For example, cars emit more volatile organic compounds per mile, while per mile large particulate matter emissions are greater with buses.

¹⁰On an equal horsepower basis, gasoline engines emit roughly 28 times as much CO as diesel engines, because the latter burn their fuel in excess air to ensure full combustion (Krivoshto et al., 2008). Particulate matter can be both released directly from engines as well as formed through chemical reactions from primary pollutants. The estimates in Cai, Burnham and Wang (2013) focus only on the former, so likely underestimate total vehicle particulate matter emissions.

¹¹In Canada, about 40% of all public transit riders make at least a portion of their journey by rail transit as opposed to bus transit. Subways and light rail typically uses electricity as an energy source. While there is heterogeneity across regions, the majority of Canada's electricity is generated by sources with no air pollution emissions. We therefore disregard emissions from urban rail transit.

Technological change dramatically improved both diesel and gasoline engine emission rates over the past decades. Figure 1 illustrates how lifetime mileage-weighted emissions changed between 1990 and 2010. In general, emissions are between 80-98% lower on a permile basis. Panel A shows how CO emissions from diesel buses fell from 7.5 grams to 1 gram per vehicle mile. Gasoline fueled cars experienced an even larger improvement, with CO emissions decreasing from roughly 15 grams to 3 grams per vehicle mile. Panels B and C display similar trends for NO_X and PM_{2.5}. The NO_X emissions from buses decreased from nearly 25 grams per mile to 2 grams per mile, while the PM_{2.5} emission rate declined from 1 gram per mile to virtually zero by 2007.

Still, while there are obvious improvements in the emission rates of both passenger vehicles and diesel buses, variation remains in their relative improvements over the period. Any improvements in air quality due to a pollution swap must arise from the *relative* reduction in bus emissions compared with cars. The dashed black lines in Figure 1 shows the time series of the relative emission rates of diesel buses and gasoline-fueled cars. Unlike the secular trend in absolute emission rates, there is no obvious pattern to relative emissions. For NO_X , both gasoline cars and diesel bus emissions have improved, yet the rate of improvement was more rapid for cars. As a result, between 2000 and 2010, NO_X per bus-mile relative to the NO_X per car-mile increased substantially. The opposite pattern is true for $PM_{2.5}$: since 2007, the figure shows a dramatic improvement in the emissions rate for diesel buses relative to gasoline cars.

The technological parameters provide clear predictions about relative emission rates per mile traveled, but neglect important behavioral adjustments made by commuters in response to observed congestion, cost of travel and other factors. Regardless of technological improvement, the overall effect of public transit availability on air quality is ambiguous since it depends on these difficult to observe variables. Consider, for instance, several prospective implications of an increase in gasoline taxes. If buses are under capacity, a gasoline tax may motivate commuters to substitute from cars to buses. No change in NO_X would be expected (as the excess bus capacity is filled), but we might observe a reduction in CO as fewer car trips are taken. This is the heart of the pollution-swap hypothesis: there is a combination of technological and behavioral parameters that imply investments in public transit can improve air quality. It is reasonable to imagine an alternative scenario, however: an identical car-to-bus substitution with an at-capacity transit system may induce more bus trips as transit authorities add buses to meet the increased demand. This would, ultimately, lead to an increase in NO_X. Moreover, incorporating the fundamental law of road congestion hypothesis (Downs, 1962; Duranton and Turner, 2011) with this at-capacity scenario, any freed road space resulting from the initial car-to-bus substitution is occupied with latent demand from passenger vehicles. The net effect then is an increase in NO_X and no change in CO. The point is that the relationship between public transit and air quality – and whether there is scope for an environmentally beneficial pollution swap – therefore depends on both technological parameters and behavioral responses. Historically it has been challenging to obtain reliable, time-varying ridership and capacity data on public transit usage. Aggregates are available, but as Anderson (2014) demonstrates, there is substantial time-dependent variation in transit demand. Use of aggregate capacity and ridership values therefore may introduce large biases in estimating the impact of transit on pollution.

A stylized model formalizes the interactions between commuter choice and technology and how these determine the relationship between changes in the characteristics of public transit and changes in emissions. A representative consumer chooses transport services (T)and other goods (X) to maximize utility (subject to a standard budget constraint):

$$U = U(T, X).$$

Transport services are provided by through public transit (B) or private cars (D), such that:

$$T = T(B, D).$$

Assuming constant elasticity of substitution functions allows us to express the demand for driving and public transit (relative to benchmark demand) as:

$$B = B(p_B, p_D, p_X) = \left(c_U^{\sigma_U} c_T^{(\sigma_T - \sigma_U)} p_B^{-\sigma_T}\right)$$
$$D = D(p_B, p_D, p_X) = \left(c_U^{\sigma_U} c_T^{(\sigma_T - \sigma_U)} p_D^{-\sigma_T}\right),$$

where c_U is the price index (general cost function for utility), c_T is the price of transport services,¹² and p_D and p_B are the price of driving and public transport, respectively.¹³ The

¹²Given the constant elasticity of substitution function adopted, $c_U = \left(\theta_X p_X^{1-\sigma_U} + \theta_T c_T^{1-\sigma_U}\right)^{\frac{1}{1-\sigma_U}}$ and $c_T = \left(\theta_D p_D^{1-\sigma_T} + \theta_B p_B^{1-\sigma_T}\right)^{\frac{1}{1-\sigma_T}}$. The θ parameters refer to benchmark cost shares.

¹³The price of driving and public transport can include both pecuniary as well as non-pecuniary components, including time costs, access costs, and other costs (Anderson, 2014; Parry and Small, 2009). In our simple model, we do not connect the demand for private transport to congestion, such that the price of public and private transport in our model is exogenous. It is possible to endogenize the price of private transport to reflect congestion costs in a simple manner, by allowing the price of private transport to be a function of

parameters σ_U and σ_T reflect the elasticities of substitution between transport and other goods and between driving and public transit, respectively. These elasticities of substitution are critical for connecting commuter behavior to public transit and air quality.

Total emissions are the sum of pollution from buses and driving:

$$E = E_B + E_D$$
$$= B\phi_B/\zeta_B + D\phi_D/\zeta_D$$

where ϕ is the per-mile emissions of pollutants from public and private vehicles, and ζ is the occupancy rate of each vehicle.¹⁴

This set-up enables us to derive an expression for the change in emissions that results from a change in the price, availability or other characteristic of public transit. (Although the empirical results later in the paper are based on a non-marginal supply shift, a price change is used in this analytical model to tractably capture changing supply conditions.) Changes in the price (availability) of public transit affects emissions as follows:

$$\frac{dE}{dp_B} = \frac{\phi_B}{\zeta_B} \frac{\partial B(p_B, p_D, p_X)}{\partial p_B} + \frac{\phi_D}{\zeta_D} \frac{\partial D(p_B, p_D, p_X)}{\partial p_B}$$

This expression contains both technological and behavioral parameters. The first right-hand side term is the product of change in the demand for bus services due to the change in the price of public transport, $\frac{\partial B(p_B, p_D, p_X)}{\partial p_B}$, multiplied by the emissions rate for public transit, $\frac{\phi_B}{\zeta_B}$. Increasing the price of transit causes transit demand to decrease, so this term is negative. The second right-hand side term is the change in car travel due to the change in public transit price, $\frac{\partial D(p_B, p_D, p_X)}{\partial p_B}$, multiplied by the emissions rate for passenger car travel, $\frac{\phi_D}{\zeta_D}$. For an increase in transit price, car demand will increase as long as cars and buses are substitutes. Hence, this term is positive. The sign of the overall change in emissions – i.e., the effect of public transit availability on air pollution – depends on the relative rate of emissions from cars compared with public transport and the magnitude of the relevant elasticities.

Given the assumed constant elasticity of substitution functional forms, it is possible to write a closed-form solution for the elasticity of transport sector emissions with respect to

traffic volume, $p_D = D^{\psi}$ (where we assume public transit does not cause congestion, for simplicity). A value of $\psi > 1$ implies that additional driving imposes costs on others, which increase the price of driving. We do not focus on this model variant, but do include a simulation results in which we allow ψ to take on positive values below.

¹⁴It is possible that vehicle occupancy rates are endogenous, but for simplicity, we do not consider that in the simple model.

public transport price, η_{Zp} . This expression is:

$$\frac{dE}{dp_B}\frac{p_B}{E} \equiv \eta_{Zp} = \theta_T \theta_B \sigma_U + \theta_B (\sigma_T - \sigma_U) - \frac{E_B}{E} \sigma_T.$$
(1)

The response in emissions following a change in the price of public transport, η_{Zp} , depends on the following parameters: the elasticity of substitution between transport services and other goods (σ_U), the elasticity of substitution between transport modes (σ_T), the cost shares of all transport (θ_T) and public transit (θ_T) and the share of public transit in total transport emissions ($\frac{E_B}{E}$).

The prospect of a pollution swap and an overall improvement in air quality from an expansion of the transit system depends on the values of these parameters. To give a sense of the magnitude and direction of the change in emissions due to a change in public transit availability, we conduct a numerical simulation. Calibrated values for these parameters are shown in Table 1. These coefficients are from several sources. Cost shares of transportation and of driving in total transportation, shown in Table 1 Panel B, are from the 2014 Canadian Survey of Household Spending.¹⁵ Panel C displays the elasticities of substitution. The elasticity of substitution between transit and driving is set at 0.4 to match an elasticity of transport demand typically found in the literature (see, for example, Litman, 2004). The elasticity of substitution between travel and other goods is chosen to generate an own-price elasticity of driving of -0.18, a value also consistent with the literature (Gillingham, 2014). The pollution rates for cars and buses are from Cai, Burnham and Wang (2013), who produce lifetime mileage-weighted emission rates for diesel buses and gasoline cars.¹⁶ The selected emission rates correspond to the 2010 model year. We assume that 40% of total transit passenger-miles are provided by (zero emission) passenger rail, and the remaining 60% are provided by diesel bus, which reflects average Canadian configuration. The mode share for public transit reflects the mode share in Canada's larger cities.¹⁷ Finally, occupancy rates of passenger cars and urban transit buses are from Office of Energy Efficiency (2014) and determined by dividing passenger kilometres of travel by vehicle kilometres of travel.

Based on these parameters, we start by simulating the change in emissions that result from doubling the price of public transit, p_B . Our econometric models are identified using

¹⁵Results are given here: http://www.statcan.gc.ca/daily-quotidien/160212/dq160212a-eng.htm.

 $^{^{16}\}mathrm{As}$ noted previously, we assume that urban rail produces no emissions.

¹⁷Public transit mode share is at or above 20% in Canada's largest cities. See https://www12.statcan. gc.ca/nhs-enm/2011/as-sa/99-012-x/2011003/c-g/c-g01-eng.cfm. Note that the cost share of transit is 0.1 and the mode share is 0.2, so by implication transit costs 2 times as much per kilometre as driving.

public transit strikes which completely remove public transit, so this does not perfectly parallel the subsequent reduced form results. Still, the simulation yields useful intuition on the scope of the effect of a large change in public transit availability.

Given the model's parameterization, the results suggest that doubling the price of public transport *reduces* NO_X emissions from the transport sector by 2.2% and *increases* CO emissions by a smaller amount equal to 1.9%. There is also a small, 0.7% reduction in $PM_{2.5}$ emissions. In other words, in the base case with realistic parameter values, one type of pollution is swapped for another: an increase in CO emissions from cars is exchanged for a decrease in NO_X emissions from buses.

As is apparent in equation (1), the scope of a pollution swap clearly depends on the elasticities of substitution. Figure 2 plots sensitivity analysis for these two parameters. The left-hand panel illustrates how much the elasticity of emissions with respect to the price of public transport changes with different values of the elasticity of substitution between public and private transport, σ_T . High values of σ_T indicate that commuters are more willing to switch between cars and buses. Buses produce more NO_X emissions than cars, so this switch entails a reduction in NO_X that is more pronounced at higher elasticities. In contrast, car travel produces more CO than bus travel, so the opposite is true for this pollutant. When consumers are unwilling to switch between buses and cars – i.e., σ_T is small - doubling the price of bus travel, unambiguously leads to improved air quality as both CO and NO_X emissions decline, hence a pollution swap can lead to improved overall air quality. Figure 2 also shows what we would expect at the benchmark values where $\sigma_T = 0.4$. The dashed line illustrates this base case. In this scenario, doubling the price of buses, reduces the demand for bus trips and hence reduces NO_X emissions. At the same time it increases the demand for car trips and associated CO emissions. Given this elasticity of substitution and other parameters values, the model predicts virtually no change in $PM_{2.5}$. The right-hand panel of Figure 2 provides similar sensitivity analysis for σ_U , the degree to which consumers reduce overall travel demand in response to an increase in bus prices. Values of σ_U greater than approximately 0.5 unambiguously reduce all types of pollution. Again however, at the benchmark parameterization, doubling the price of buses predicts less NO_X pollution, a slight increase in CO pollution, but little change in $PM_{2.5}$.

Table 2 reports additional sensitivity analyses where we vary assumptions about bus and car occupancy rates, elasticities of substitution between travel and other goods and between driving and transit, congestion feedback, as well as the share of rail in benchmark public transport. These results suggest that, in general, increases in the price of public transit reduce NO_X emissions, but increase CO emissions. For instance, if we double the occupancy rate of buses, ζ_B , from 12.5 to 25, and then double the price of bus travel, NO_X falls by 0.3% while CO increases by 2.0%. This NO_X-for-CO pattern is maintained across most parameter combinations. Effects on PM_{2.5} emissions are ambiguous and depend on model parameters. In the final row of the table, we allow the price of driving to respond to the quantity of driving, to roughly reflect congestion. This model crudely captures the "fundamental law of road congestion," which suggests that driving volumes are unchanged due to transit provision (Duranton and Turner, 2011).¹⁸ In this scenario, changes in the price of public transit have little impact on the demand for driving, and the results suggest that all three pollutants experience declines due to increases in public transport price. In other words, under most plausible scenarios, the best that investment in public transit can do is to swap one type of pollutant for another, but unambiguous improvements in air quality due to investments in public transit are unlikely. The next section then aims to to measure what actually happens to air quality what transit is temporarily eliminated due to transit strikes.

3 Empirical Approach

The analytical model illustrates the mechanism linking public transit to air quality. This channel relies on several hard-to-identify parameters. We therefore investigate the reduced form relationship between transit and air quality using good-as-random variation in transit availability. We first present our econometric strategy and then discuss the data.

3.1 Econometric Strategy

Transit strikes, where public transit systems cease operations due to labor negotiations, produce a quasi-random variation in transit availability. This allows the effect of transit availability on air pollution to be cleanly identified. Transit strikes typically reduce public transit service to near zero in a local region¹⁹ and, as transit strikes are temporary, they

¹⁸Duranton and Turner (2011) research focuses on the long run, while our empirical analysis is a short-run analysis. We include this scenario for completeness.

¹⁹Often public transit authorities will continue to provide service to elderly and special needs commuters. In one case that we know of included in our sample (the Vancouver public transit strike in 2001), transit strikes shut down bus public transit but subway public transit was unaffected. Further, it is possible for private firms to provide temporary services in the absence of publicly-provided transit, but private operators are rare in Canada. Given that public transit may not be fully eliminated, our estimates should be interpreted as conservative (lower bound), intent-to-treat effects that result from imperfect compliance.

are unlikely to induce residential sorting. Moreover, while transit work actions potentially affect traffic and air pollution in a region, they are unlikely to be affected by air pollution, so causality is uni-directional.²⁰ Transit strikes are therefore an exogenous source of variation in transit availability that allows the short-run effect of public transit on air pollution to be recovered.

There is an important caveat to this source of identifying variation however. This identification strategy yields the *short-run* response to a change in public transit availability. This short-run response does not perfectly map onto long-run outcomes and, in general, it is the long-run impact of public transit investment that is important from a public policy perspective. Yet, as mentioned, it is empirically challenging to estimate the long-run response of air pollution to changes in public transit and the bulk of research on this topic estimates shortrun effects (e.g., Bauernschuster, Hener and Rainer, 2017; Chen and Whalley, 2012). While our estimates are not the ideal policy-relevant parameter of interest, we do believe that the plausibility of identification nevertheless allows us to provide useful results. In addition, the setting of our results enables us to build on prior research that identifies short-run outcomes. For example, Bauernschuster, Hener and Rainer (2017) use extremely short transit strikes (less than a day; typically one to two hours) to reach conclusions about the relationship between air pollution and transit availability. These very short-run responses may differ quite significantly from our longer-run responses to changes in public transit. Likewise, Chen and Whalley (2012) use a regression discontinuity design to measure the impact of a subway opening on air pollution in China. Given this design, identification comes from the immediate change in air pollution following a subway opening. In our study, many of the transit strikes last for several weeks and, as a result, induce behavioral responses that can be contrasted with those of Bauernschuster, Hener and Rainer (2017) and Chen and Whalley (2012) as estimates that more closely parallel the long-run responses of interest.

Our primary empirical specification employs fixed effects to control for selection on unobservables, by leveraging a large dataset comprised of daily (and hourly) air pollution data in multiple cities across multiple years. We estimate the effect of public transit strikes on the ambient concentration of pollution emissions by comparing measured pollution concentrations during a strike with pollution concentrations in the same city in the same year when no strike is in place and on the same date in other cities with operating transit. We then interpret the coefficient on our strike variable as the effect of an exogenous change in local

 $^{^{20}}$ Although transit strikes are likely strategically timed, we can condition on observable determinants of timing, as we discuss below, such that we argue that transit strikes are conditionally exogenous.

transit availability on air quality.

Our main specification is:

$$E_{cymd} = \delta \cdot \text{strike}_{cymd} + W_{cymd}\beta + \phi_{cy} + \theta_{ymd} + \epsilon_{cymd}.$$
 (2)

where E_{cymd} , the dependent variable, is average daily NO_X, CO, or PM_{2.5} pollution concentrations in city c in a particular year, y, month, m, and day, d^{21} It is important to highlight a key difference between (2) and the discussion in Section 2. The model in the prior section focused on transport sector *emissions*, whereas this econometric model uses ambient pollution *concentrations* as a dependent variable (we use the same notation for each). The two are related, but cities have other sources of emissions in addition to those from the transportation sector and other variables such as weather affect pollution concentrations. So there is an imperfect correlation between emissions and concentrations.

strike_{cymd} is a dummy variable that takes a value of one if there is a transit strike on a specific date, *ymd*, in municipality c, and zero otherwise. Our coefficient of interest is δ . δ measures the change in pollution as a result of a transit strike. This can be interpreted as the negative of the short-run change from an expanded public transit system. δ is a reduced form coefficient that incorporates the behavioral and technological factors that govern the relationship between buses, private vehicles, and air pollution. We estimate the model separately for NO_X, CO and PM_{2.5}, obtaining separate δ coefficients for each. Further, while equation (2) is our preferred specification, we vary the resolution of our fixed effects in robustness checks as a test of the sensitivity of our results to alternative identifying assumptions.

There are a series of other variables in (2). W_{cymd} is a vector of weather covariates including daily maximum temperature, mean temperature, mean temperature squared, minimum temperature, daily precipitation and precipitation squared. Including weather is important because air pollutants, once released, can be catalyzed by sun and high temperature. Moreover, precipitation can remove air pollution from the atmosphere. Conditioning on weather further helps to address potential bias in coefficients that could be introduced if transit authorities plan transit strikes to take advantage of particular weather events (for instance, choosing to start a strike on a day when poor weather is forecast).²² ϕ_{cy} is a city-by-year variable that captures time-varying city-specific trends. General economic and labor market

²¹While the main results use daily data, we also include results that use hourly pollution data.

²²In an unreported robustness check, we test the sensitivity of our results to omitting all weather covariates. The coefficient on strikes is not significantly affected by this change.

conditions influence pollution emissions (and hence concentrations), so this effect controls for these unobservables. θ_{ymd} is a day-of-sample fixed effect that captures other time-varying confounders that are common across our panel. Holidays, for example, tend to have less traffic than normal workdays. There is also seasonality in pollution variation and θ_{ymd} helps to capture these time-varying unobservables. ϵ_{cymd} is an error term. All standard errors are clustered at the city level allowing for arbitrary temporal correlation in error term.

The identifying assumption in (2) is that, conditional on included covariates, the specific timing of strikes in each municipality is as good-as-randomly assigned. In other words, we assume that the timing of strikes is not chosen in response to (or correlated with) observed or predicted levels of air pollution. On the whole, this assumption is mild, but potential violations could occur if strikes were timed to create maximum disruption for a city, for example by holding a strike on the first day of September (when students return to school). The data suggest that this is not the case: there is no statistical pattern to the start date of strikes in the data (results are presented below). More importantly, our empirical strategy, which includes date fixed effects, controls for the variation in pollution concentrations by date (there is a separate fixed effect for every day of the sample in our preferred specification). In addition, to measure the sensitivity of our results to this identifying assumption, we conduct falsification tests where we implement "fake" strikes, which are shifted in time relative to the "real" strikes we observe in our data. We expect and find no effect due on pollution emissions attributable to a "fake" strike in these placebo models.

3.2 Data

Our research design requires data on air pollution, weather and work actions. These are assembled from several sources.

Air pollution data are from Canada's National Air Pollution Surveillance Program (NAPS).²³ NAPS was established to provide long-term air quality data at a uniform standard from across Canada. Launched in 1969 with 36 air quality monitoring stations, it has expanded significantly over time. Our data spans 1974 through 2011 for 18 municipalities for CO. For NO_X, it runs from 1980 through 2011 for 13 cities. Measurement of PM_{2.5} runs from 1997 through 2011 for 9 municipalities.²⁴ NAPS monitoring stations measure ambient pollution

²³A description of NAPS, along with supporting documentation regarding monitoring protocols and station locations, is available at Environment Canada's website: http://www.ec.gc.ca/rnspa-naps/Default.asp?lang=En&n=5C0D33CF-1.

²⁴These include Toronto, Montreal, Vancouver, Ottawa, Calgary, Edmonton, Hamilton, Quebec City, Kitchener-Waterloo, London, Victoria, Oshawa, St. Catherines, Halifax, Windsor, Saskatoon, Regina, Win-

concentrations for a large number of substances. Most stations continuously monitor CO, NO_X , ground level ozone, sulfur dioxide and particulate matter (PM_{10} and $PM_{2.5}$). Air samples are also periodically analyzed at a central lab facility to identify cumulative levels of over 100 additional substances. We focus on CO, NO_X and $PM_{2.5}$ as these are the primary pollutants commonly emitted by vehicles.²⁵

Assembling the dataset required assigning pollution monitoring stations to cities. Figure 3 illustrates the procedure for mapping monitoring stations to city centers. Air pollution monitoring stations are given as black crosses. Fixed radii circles were drawn around each city centre (as measured by the coordinates of the City Hall). The top panel shows both the dispersion of monitoring stations and cities in our data. The bottom panel provides an example of the fixed radii mapping assignment of stations to cities. For several small cities, only a single monitoring station is captured within the circle. Larger cities such as Toronto and Vancouver have several monitoring stations recording air quality. In these cases, the closest monitoring station to city centre is used. As NO_X and $PM_{2.5}$ disperse easily while CO is a local pollutant (Gaur et al. (2014) and Rattigan et al. (2010)), we further investigate the sensitivity of our analysis to the choice of pollution monitoring stations, by estimating results on a sub-sample of monitoring stations that are within 2 kilometres of major thoroughfares. In robustness checks, we also test the sensitivity of our results to different ways of assigning pollution monitors to cities. In particular, we use the inverse-distance weighted average of all pollution monitoring stations within 5 and 10 miles of the city centre, rather than simply assigning the closest monitor to the city centre. We show that our results are not affected by the choice of assignment mechanism.

Information on transit strikes are from Employment and Social Development Canada's Workplace Information Division. This division tracks collective agreements and maintains a database of all work stoppages categorized according to North American Industry Classification System (NAICS) codes. We use NAICS code 485110: urban transit systems. Our data on work stoppages capture, among other variables, the dates that the action began and

nipeg and St. John's. Cities range in size from approximately 5 million inhabitants (Toronto) to 0.2 million (St. John's). Montreal, Quebec City and Victoria are excluded from the NO_X analysis as data are missing for these cities. The differences in the number of cities across samples is attributable to the absence of strikes in some municipalities for periods in which we have air pollution data.

 $^{^{25}}$ Ozone is a key vehicle-related pollutant as well. However, ozone is not released directly by vehicles but instead forms from a reaction between NO_X and volatile organic compounds in the presence of sunlight and heat (i.e., it is not a primary pollutant). The chemical transformation is highly non-linear, and so predicting and modeling the effect of vehicles on ozone emissions is challenging. For this reason, we focus on primary pollutants in this study.

ended, the number of workers affected, the location and the names of the transit corporation as well as the union. There were 105 municipal transit strikes between 1974 and 2011. There is little systematic tendency for strikes to occur in any particular season and, given gaps in pollution data, not all strikes are common across pollutants. Figure 4b plots the number of observed and initiated strikes (i.e., the first day of work stoppage) for each month. The figure shows roughly 8.75 strikes have been initiated in each month. Visually there appears to be a slight tendency for strikes to start in Fall, but this tendency is not statistically significant.²⁶ Our regressions use a variety of fixed effects to control for most systematic seasonal trends. On average each strike lasts for 19.19 days, with a minimum of 1 day and a maximum of 87 days. Figure 4a illustrate a histogram of strike lengths over all cities while Figure 4c shows the cross-sectional variation in observed strikes by city. As shown, over the period of 1974 to 2011 there were 57 observed strikes in Montreal while only 1 strike occurred in Regina.

Measurement of pollution is correlated with weather. Data on meteorological conditions are obtained from Environment Canada.²⁷ To control for the effect of weather conditions on the ambient air pollution, polynomials of maximum, minimum and mean temperature as well as precipitation are included. As with the NAPS monitoring stations, meteorological conditions are assigned to city centers using information from the closest weather stations.

Table 3 presents some key information for the NO_X , CO, and $PM_{2.5}$ in our sample. There are three panels. Panel A presents an overview of the sample. There are 11,216 unique days for 13 cities in the NO_X sample. For CO, there are 18 cities and 13,038 days. Pollution monitors require maintenance and occasionally fail to record the level of ambient pollution. The NAPS system records these as missing values which we drop from our analysis. We are unaware of any systematic bias associated with these missing values. There are 944 strike work-days in our NO_X and 411 stoppage days in our $PM_{2.5}$ sample, a considerable reduction from the 2,155 in the CO sample. A shorter period of analysis and the lack of NO_X data for cities in Quebec account for the reduced number of strike days.

Panel B presents summary statistics for our dependent and weather variables. The mean NO_X concentration is 35.97 parts per billion (ppb) with a standard deviation of 31.52. For CO, the mean value is 0.96 parts per million (ppm) with a standard deviation of 0.98. For PM_{2.5} the mean value is 7.80 μ/m^3 with a standard deviation of 6.38.

Finally, Panel C shows the residual variation in the dependent variable after it is re-

²⁶A Pearson Chi-squared test fails to reject the null hypothesis of equal proportions of strikes by month: $\chi^2 = 14.09, df = 11, p = 0.22.$

²⁷Climate data is available at Environment Canada's website: http://climate.weather.gc.ca/.

gressed on the suite of fixed effects and weather controls from (2). These include NAPS-year and day-of-sample fixed effects as well as maximum, minimum and mean city-specific daily temperatures, a quadratic in mean temperature, precipitation and a quadratic in precipitation. Even with this rich set of fixed effects, substantial residual variation is apparent. Fixed effects and weather explain 47% of the variation in NO_X , 65% of the variation in CO and 41% of the variation in $PM_{2.5}$.

4 Results

Four sets of results are presented. We first provide our main results plus several robustness checks. We then examine intra-day heterogeneity and the implications of public transit on maximum daily pollution readings. Next, technological change has had a large role in the relationship between transit and air quality, so we separately examine pre- and post-2000 effects. Finally, we show selected falsification tests. Throughout, the message is consistent: public transit increases ambient NO_X concentrations while having little to no effect on CO or $PM_{2.5}$.

4.1 Main results

Table 4 shows the main results using the daily mean pollution level as the dependent variable. Nine columns are presented, three for each pollutant. The different columns alter the source of identifying variation by using different combinations of time and location fixed effects. All standard errors are clustered at the city level to control for arbitrary temporal correlation in error term.²⁸

Columns (1) to (3) of Table 4 show results for NO_X emissions, with all three columns showing stable estimates. In (1), using date and NAPS-year fixed effects, the removal of transit improves ambient NO_X concentrations by 3.8ppb. The corresponding models for CO and PM_{2.5} are in columns (4) and (7). A transit strike leads to a 0.02ppm increase in CO, but the standard error is large. Likewise, removing buses reduces PM_{2.5} by 0.8 $\mu g/m^3$, again with a large standard error.

Changing the source of identifying variation has little influence on any of the point

²⁸Models are also run that allow for spatial correlation by clustering on year-month and temporal and spatial correlation by clustering at city-year and city and year. The standard errors are smaller than those obtained by clustering by NAPS monitoring station suggesting that the confidence intervals presented here may be conservative.

estimates or standard errors. Columns (2) and (3) show that a strike is associated with statistically significant decrease of 3.77 to 3.98 ppb in NO_X concentrations. In (5) and (6), CO concentrations still increase with transit strikes, but again the parameters are imprecisely estimated. Finally, removal of public transit leads to a decrease in PM_{2.5} of 0.5 to 0.8 $\mu g/m^3$, but this reduction is not statistically distinguishable from zero.

It is worth noting that the estimates from the econometric models corroborate those generated from the simulation model. Table 3 shows that the mean NO_X concentration in our data is 36.0 ppb, so a 3.8 ppb reduction suggests that removal of transit reduces NO_X by approximately 10%. This is of similar magnitude, albeit slightly larger, than the estimates presented in Table 2 which reflect a non-complete removal of publicly provided transit. Further, while the point estimates on CO concentrations are not distinguishable from zero, the econometric model implies a roughly 2% reduction in CO concentrations due to buses. Again, this is approximately within the range of the values in Table 2. Similar to the CO estimates, the PM_{2.5} coefficients are imprecise. Moreover, Table 2 does not provide a clear prediction on the magnitude or sign of a change in PM_{2.5}. The imprecision of the econometric point estimates care, yet, the general pattern of results suggests that a pollution swap – NO_X for CO – is possible. Unfortunately, the strongest conclusion emerging from our results is that NO_X is reduced when public transit service is cut; we cannot be unequivocal in our assertions about CO given the impreciseness of the estimates.

Sensitivity to Pollution Monitor Assignment

As described in Section 3, we impute a city's pollution level by using the value from the closest monitor to the city centre. Table 5 uses three alternative methods of assigning pollution to cities. Column (1), (3) and (7) use the inverse-distance weighted average values of all monitors within 5 mile radius of city centroids. Columns (2), (5) and (8) use the inverse-distance weighted average within a larger 10 mile radius for each pollutant. Finally, column (3), (6) and (9) restrict the analysis to monitors near major thoroughfares. NO_X and PM_{2.5} disperse more easily while CO is a local pollutant, so the location of the pollution monitor has the potential to notably influence the results.

The NO_X estimates are consistent with Table 4. The coefficients show a reduction of between 3.6 and 3.9ppb in NO_X concentrations associated with a public transit strike. Precision remains a problem for CO and $PM_{2.5}$. While the sign and magnitude of the point estimates are similar to the models in Table 4, the confidence intervals are wide and include zero. Monitor assignment is immaterial to the results.

4.2 Hourly Pollution Concentrations

Strikes vary at the daily level in our data, so our preferred models concentrate on daily average pollution levels. Intra-day heterogeneity, especially with respect to heavy traffic periods, may however have distinct patterns that are not captured by the daily average.

To investigate this intra-day heterogeneity, we estimate (2) for each of the 24 hours in a day, where, for instance, the 7:00am interval represents the hour from 7:00 to 7:59am. Rather than using daily average pollution concentration as the dependent variable, the pollution concentration for that specific hour is used. All control variables remain the same. In particular, we use our preferred specification, which includes weather controls, date fixed effects and pollution monitor-year fixed effects. Separate regressions are conducted for each of NO_X, CO, and PM_{2.5} for each hour.

Figure 5 plots the point estimates from these regressions. A transit strike causes a statistically significant reduction in atmospheric NO_X concentrations throughout the day. These reductions are only statistically significantly different than zero during the standard workday however. Outside of the 7:00am to 5:00pm stretch, the parameters are too imprecise to be statistically distinguishable from zero. The patterns for CO and $PM_{2.5}$ illustrate the difficulty in making claims about these pollutants. In both cases, the point estimates, which are signified by the dark circles, fluctuate around zero, while the error bars are wide. It does appear, however, that CO increases during the morning and afternoon travel peak in response to a strike, while $PM_{2.5}$ decreases (although, as shown by the figure, coefficients are not statistically significant). In general, these hourly regressions reinforce the results from the earlier tables: public transit increases NO_X pollution but has little effect on CO or $PM_{2.5}$.

The results in Figure 5 suggest that removing public transit has larger effects on atmospheric pollution concentrations during rush hours. Table 6 looks at this from a slightly different perspective. It presents results using the daily maximum pollution concentration as the dependent variable. Daily maximum pollution levels typically occurs during rush hour periods, but this is not strictly the case. Columns (1) to (3) show point estimates for the effect of a transit strike on daily maximum pollution readings. Several elements of these models are worth highlighting. First, compared with the preferred specifications in Table 4, the point estimates are notably larger. The strike coefficient in the NO_X model has nearly doubled. For CO, the point estimate is seven times larger when using daily maximum pollution than in Table 4, while the parameter on $PM_{2.5}$ increased nearly threefold. Statistical significance remains elusive of CO and $PM_{2.5}$. Further, given the disproportionate increase in the standard error in the NO_X model, we are able to claim less about the effect of public transit on daily maximum pollution concentrations. It is only possible to reject a null hypothesis of no effect at a 10% level. Nonetheless, the results do tend to support the general inference that public transit does little to improve local air quality.

4.3 Transit Strikes and Technological Change

In the discussion of the analytical model, we highlighted the large changes in transportation technology over the past 20 years. During this period, both cars and buses became substantially cleaner. In this section, we examine whether these changes in technology are observable in the data. In particular, we sub-divide our sample into two periods – pre-2000 and post-2000.²⁹ We then conduct separate regressions on each of these sub-samples.

Figure 1 provides suggestive predictions for the results. While, say, the NO_Xemission rate for both cars and buses improved, the relative performance for buses compared to cars fluctuated over time. In the pre-2000 period, buses emitted between 10 to 25 times more NO_X compared to cars. After 2000, this ratio spikes to more 40 times on a per mile basis before declining.³⁰ Thus we might expect the impact on a strike on NO_X to be larger after 2000 even though post-2000 buses are cleaner than pre-2000 buses. This prediction is confirmed in Table 7. Columns (1) and (4) illustrate the effect of a transit strike on NO_X pollution before and after 2000, respectively. A work stoppage leads to a small 0.3 ppb reductin in NO_X in the early period. The latter period shows a much larger effect of 10.1 ppb.

The opposite is pattern holds for $PM_{2.5}$. Figure 1 suggests a continuous performance improvement in the emissions rate of buses relative to cars post-2000. We therefore expect a transit strike to have a beneficial impact on $PM_{2.5}$ before 2000 and less so later in the sample. Again, this prediction is confirmed in Table 7, which indicates a statistically significant reduction in $PM_{2.5}$ of 3.7 $\mu g/m^3$ before 2000. After 2000, the coefficient is not meaningfully different from zero.

Results for CO are less intuitive. Figure 1 suggests a large improvement in CO emissions for buses relative to cars during the latter period of our sample, so we expect that a transit strike will have more detrimental impacts on CO later in the sample. This is not what

²⁹We choose this date as it roughly represents the mid-point of our observations over all three pollutants.

³⁰It is important to note that the emissions rates presented in Figure 1 are a mileage-weighted average over a vehicle's entire lifetime, not average emissions rates for the on-road vehicle stock (which we do not observe). As a result, the temporal correspondence between emissions from on-road transit and predicted lifetime-weighted emissions rates is unlikely to be perfect.

we find. Instead, Table 7 shows that after 2000, a transit strike yields a *reduction* in CO emissions, suggesting that transit increases emissions. These coefficients are at odds with the technological predictions.³¹ Yet, it is important to emphasize that the coefficient on the pre-2000 CO impact is not precisely estimated and the sign on the post-2000 period reinforces the general conclusion that public transit does not improve local air quality.

4.4 Placebo Models

Table 3 shows substantial residual variation in pollution concentrations even after controlling for a wide array of fixed effects. One concern with our research design may be that the transit strike indicator is actually capturing other systematic unobservable variables. We claimed that transit strikes *caused* a change in NO_X concentrations but had no statistically identifiable causal effect on CO or PM_{2.5}. Table 8 probes this claim via a falsification test, whose motivation is that we should not observe an effect where we do not expect one.

Table 8 presents three columns of results for placebo transit strikes, where we time shift strikes in the dataset. We replace our real strike variable with a fake strike variable that occurs exactly one calendar year later. Column (1) shows the effect of the placebo transit strike on NO_X. The coefficient remains negative but is less than one third the magnitude of our preferred specification and is not statistically distinguishable from zero. For CO, the point estimate actually increases in magnitude, but remains statistically insignificantly different from zero. Finally, for PM_{2.5} the point estimate is of a different sign from the estimates in Table 4 and is likewise imprecise. Notwithstanding the residual variation in the dependent variables, we do not appear to detect an effect where one is not expected. We view this as corroborating our conclusions and as support the causal interpretation of the main models.

5 Conclusion

This paper measures the effect of public transit on air quality in 18 major Canadian cities. Transit strikes are used to identify the causal short-run effect of buses on local air pollution. Our main result is that removing public transit causes a 3.5 part per billion, or about 10%, short-run reduction in ambient NO_X concentrations. These reduced form results are

 $^{^{31}}$ The scenario in Table 2 in which we crudely simulate congestion yields predictions that are closer in line with these findings.

robust to different methods of assigning pollution to cities, to several distinct sources of identifying variation and also holds up to placebo tests. A calibrated simulation model further suggests that it possible for transit strikes to improve air quality via a pollution swap, but demonstrates that environmentally advantageous swaps are unlikely to observed at benchmark values in North America. Overall, this study suggests that, in contrast to existing studies that take place in European cities or focus on the expansion of subways, increasing public transit capacity in it's current configuration in North America is unlikely to improve local air quality.

Bibliography

- Aftabuzzaman, Md, Graham Currie, and Majid Sarvi. 2010. "Evaluating the congestion relief impacts of public transport in monetary terms." *Journal of Public Transportation*, 13(1): 1.
- Anderson, Michael L. 2014. "Subways, strikes, and slowdowns: The impacts of public transit on traffic congestion." *American Economic Review*, 104(9): 2763–96.
- Bauernschuster, Stefan, Timo Hener, and Helmut Rainer. 2017. "When labor disputes bring cities to a standstill: The impact of public transit strikes on traffic, accidents, air Pollution, and health." *American Economic Journal: Economic Policy*, 9(1): 1–37.
- **Beaudoin, Justin, and Cynthia Lin Lawell.** 2016. "Is public transit's "green" reputation deserved? Evaluating the effects of transit supply on air quality." Working paper, University of California at Davis.
- Beaudoin, Justin, Y Hossein Farzin, and C-Y Cynthia Lin. 2014. "Evaluating Public Transit Investment in Congested Cities." Working paper, University of California at Davis.
- Beaudoin, Justin, Y Hossein Farzin, and C-Y Cynthia Lin Lawell. 2015. "Public transit investment and sustainable transportation: A review of studies of transit's impact on traffic congestion and air quality." *Research in Transportation Economics*, 52: 15–22.
- **Bel, Germà, Maximilian Holst, et al.** 2015. "Evaluation of the Impact of Bus Rapid Transit on Air Pollution." University of Barcelona, Research Institute of Applied Economics.
- Bharadwaj, Prashant, Matthew Gibson, Joshua Graff Zivin, and Christopher Neilson. 2017. "Gray matters: fetal pollution exposure and human capital formation." Journal of the Association of Environmental and Resource Economists, 4(2): 505–542.
- Cai, H, A Burnham, and M Wang. 2013. "Updated emission factors of air pollutants from vehicle operations in GREETTM using MOVES." Argonne National Laboratory.
- Chang, Tom, Joshua Graff Zivin, Tal Gross, and Matthew Neidell. 2016. "Particulate Pollution and the Productivity of Pear Packers." American Economic Journal: Economic Policy, 8(3): 141–69.

- Chay, Kenneth Y, and Michael Greenstone. 2003. "The impact of air pollution on infant mortality: Evidence from geographic variation in pollution shocks induced by a recession." *Quarterly Journal of Economics*, 118(3): 1121–1167.
- Chen, Yihsu, and Alexander Whalley. 2012. "Green Infrastructure: The effects of Urban mass transit on air quality." American Economic Journal: Economic Policy, 3(4): 58–97.
- Currie, Janet, and Matthew Neidell. 2005. "Air pollution and infant health: What can we learn from California's recent experience." *Quarterly Journal of Economics*, 3(120): 1003–1030.
- Currie, Janet, and W Reed Walker. 2011. "Traffic congestion and infant health: Evidence from E-ZPass." American Economic Journal: Applied Economics, 1(3): 65–90.
- Currie, Janet, Eric A Hanushek, E Megan Kahn, Matthew Neidell, and Steven G Rivkin. 2009. "Does pollution increase school absences?" The Review of Economics and Statistics, 91(4): 682–694.
- **Downs, Anthony.** 1962. "The law of peak-hour expressway congestion." *Traffic Quarterly*, 16(3).
- Duranton, Gilles, and Matthew A Turner. 2011. "The fundamental law of road congestion: Evidence from US cities." *American Economic Review*, 101(6): 2616–2652.
- Friedman, Michael S, Kenneth E Powell, Lori Hutwagner, LeRoy M Graham, and W Gerald Teague. 2001. "Impact of changes in transportation and commuting behaviors during the 1996 Summer Olympic Games in Atlanta on air quality and childhood asthma." Jama, 285(7): 897–905.
- Gaur, Abhishek, SN Tripathi, VP Kanawade, Vinod Tare, and SP Shukla. 2014. "Four-year measurements of trace gases (SO2, NOx, CO, and O3) at an urban location, Kanpur, in Northern India." *Journal of Atmospheric Chemistry*, 71(4): 283–301.
- Gendron-Carrier, Nicolas, Marco Gonzalez-Navarro, Stefano Polloni, and Matthew A Turner. 2017. "Subways and urban air pollution."
- **Gillingham, Kenneth.** 2014. "Identifying the elasticity of driving: evidence from a gasoline price shock in California." *Regional Science and Urban Economics*, 47: 13–24.

- Hilber, Christian AL, and Charles Palmer. 2014. "Urban development and air pollution: Evidence from a global panel of cities." *Grantham Research Institute on Climate Change and the Environment Working Paper series.*
- Jerrett, Michael, Rob McConnell, Jennifer Wolch, Roger Chang, Claudia Lam, Genevieve Dunton, Frank Gilliland, Fred Lurmann, Talat Islam, and Kiros Berhane. 2014. "Traffic-related air pollution and obesity formation in children: A longitudinal, multilevel analysis." *Environ Health*, 13(1): 49.
- Knittel, Christopher R, Douglas L Miller, and Nicholas J Sanders. 2011. "Caution, drivers! Children present: Traffic, pollution, and infant health." National Bureau of Economic Research.
- Krämer, Ursula, Thilo Koch, Ulrich Ranft, Johannes Ring, and Heidrun Behrendt. 2000. "Traffic-related air pollution is associated with atopy in children living in urban areas." *Epidemiology*, 11(1): 64–70.
- Krivoshto, Irina N, John R Richards, Timothy E Albertson, and Robert W Derlet. 2008. "The toxicity of diesel exhaust: implications for primary care." *The Journal of the American Board of Family Medicine*, 21(1): 55–62.
- Künzli, Nino, Reinhard Kaiser, Sylvia Medina, M Studnicka, Olivier Chanel, Paul Filliger, Max Herry, F Horak, V Puybonnieux-Texier, Philippe Quénel, et al. 2000. "Public-health impact of outdoor and traffic-related air pollution: A European assessment." The Lancet, 356(9232): 795–801.
- Lalive, Rafael, Simon Luechinger, and Armin Schmutzler. 2013. "Does Supporting Passenger Railways Reduce Road Traffic Externalities?"
- Lavy, Victor, Avraham Ebenstein, and Sefi Roth. 2014. "The Impact of Short Term Exposure to Ambient Air Pollution on Cognitive Performance and Human Capital Formation." National Bureau of Economic Research.
- Levy, Jonathan I, Jonathan J Buonocore, and Katherine Von Stackelberg. 2010. "Evaluation of the public health impacts of traffic congestion: a health risk assessment." *Environmental health*, 9(65): 1–12.
- Litman, Todd. 2004. "Transit price elasticities and cross-elasticities." Journal of Public Transportation, 7(2): 3.

- Neidell, Matthew. 2009. "Information, Avoidance behavior, and health the effect of ozone on asthma hospitalizations." *Journal of Human Resources*, 44(2): 450–478.
- Office of Energy Efficiency. 2014. "Comprehensive Energy Use Database."
- Parry, Ian WH, and Kenneth A Small. 2009. "Should urban transit subsidies be reduced?" American Economic Review, 99(3): 700–724.
- Rattigan, Oliver V, H Dirk Felton, Min-Suk Bae, James J Schwab, and Kenneth L Demerjian. 2010. "Multi-year hourly PM 2.5 carbon measurements in New York: diurnal, day of week and seasonal patterns." *Atmospheric Environment*, 44(16): 2043–2053.
- Sharman, Jon. 2016."Paris makes all public transport free in years'." battle against 'worst air pollution for 10Independent, "http://www.independent.co.uk/news/world/europe/paris-public-transport-free-airpollution-spike-a7460191.html".
- Toronto Environmental Alliance, TEA. 2010. "Clearing the Air on the TTC." "http://www.torontoenvironment.org/campaigns/transit/clearingtheair".
- Winston, Clifford, and Vikram Maheshri. 2007. "On the social desirability of urban rail transit systems." *Journal of Urban Economics*, 62(2): 362–382.
- Xia, Ting, Monika Nitschke, Ying Zhang, Pushan Shah, Shona Crabb, and Alana Hansen. 2015. "Traffic-related air pollution and health co-benefits of alternative transport in Adelaide, South Australia." *Environment international*, 74(1): 281–290.
- Zivin, Joshua S Graff, and Matthew J Neidell. 2012. "The impact of pollution on worker productivity." *American Eeconomic Review*, 102(7): 3652–3673.

Figures



Figure 1: Per-Mile Lifetime Mileage-Weighted Emission Rates

Continuted on following page...



Figure 1: Per-Mile Lifetime Mileage-Weighted Emission Rates. Continued from previous page.

The red and blue solid lines indicate the emission rate of diesel transit buses and gasoline passenger vehicles, respectively, and correspond to the left axis. The dashed black line measures the relative per mile bus to car emissions and corresponds to the right axis.

Notes: Source: Cai, Burnham and Wang (2013).



Figure 2: Elasticity of Pollution Emissions With Respect to Price of Public Transport

Notes: The vertical dashed lines indicate assumed benchmark elasticities of substitution.



Figure 3: Mapping Pollution Stations to Cities

Notes: Each city in our analysis is represented by a circle while air pollution monitoring stations are black crosses. Pollution monitoring stations were mapped to cities according to several weighting procedure according to their distance from each city's center.



(c) Cross-Sectional Distribution of Strikes

Figure 4: Duration, Frequency and Distribution of Strikes Across Cities and Months



Figure 5: Change in Hourly Pollutant Concentration due to Transit Strike

This figure plots point estimates from hourly regressions for each of the 24 hours in the day, using the level of pollution concentration in that hour as the dependent variable. Gray whiskers are 95% confidence intervals.

Tables

Table 1: Parameters used to Calibrate Simulation Model

Symbol	Value	Description
A. Pollu	tion rate	es
ϕ_B^{NOX}	1.31	Per mile diesel bus NO_X emissions (g/mile)
ϕ_D^{NOX}	0.12	Per mile gasoline passenger car NO_X emissions (g/mile)
ϕ_B^{CO}	1.10	Per mile diesel bus CO emissions (g/mile)
ϕ_D^{CO}	2.87	Per mile gasoline passenger car CO emissions (g/mile)
ϕ_B^{PM25}	21.8	Per mile diesel bus $PM_{2.5}$ emissions (mg/mile)
ϕ_D^{PM25}	7.1	Per mile gasoline passenger car $PM_{2.5}$ emissions (mg/mile)
-	0.4	Share of public transit miles provided by passenger rail
B. Cost	shares a	nd operational parameters
θ_X	0.8	Cost share for other goods
$ heta_T$	0.2	Budget share for transport
$ heta_D$	0.9	Cost share of driving in transport
θ_B	0.1	Cost share of transit in transport
ζ_B	12.5	Bus occupancy
ζ_D	1.58	Car occupancy
γ_B	0.2	Bus mode share
C. Beha	vioural p	parameters
σ_U	0.2	Elasticity of substitution between transport and other goods
σ_T	0.4	Elasticity of substitution between transit and driving

Scenario	Δ NOX	$\Delta \text{ CO}$	Δ PM2.5
Baseline	-2.2%	1.9%	-0.7%
$\zeta_B = 25$	-0.3%	2.0%	-1.3%
$\zeta_D = 1$	-0.8%	1.9%	1.2%
$\sigma_U = 0.4$	-3.5%	0.5%	-0.7%
$\sigma_T = 0.8$	-2.8%	4.5%	2.4%
No rail	-4.3%	1.7%	0.1%
$\psi = 100 \text{ (congestion)}$	-3.8%	-0.1%	-1.2%

Table 2: Sensitivity of the Simulation Model to Calibrated Parameters

The results show the simulated change in transportation sector NO_X, CO and PM_{2.5} emissions that result from a doubling of public transit fares. "No rail" is a simulation where all public transport is provided by bus, with no rail public transport. $\psi = 100$ is a simulation in which the price of driving is endogenous with the elasticity of price with respect to driving given by ψ .

Panel A – Overview of Sample			
	NO_{X}	CO	$\mathrm{PM}_{2.5}$
Days in sample	11,216	$13,\!038$	4,964
Number of strike-days	944	$2,\!155$	411
Number of strikes	83	105	25
Number of cities	13	18	9

Table 3: Key Information on Samples for NO_X , CO and $PM_{2.5}$ Concentrations

Panel B – Summary Statistics

	Mean	$Std \ Dev$	
$NO_X (ppb)$	35.97	31.52	
CO (ppm)	0.96	0.98	
$PM_{2.5} (\mu/m^3)$	7.80	6.38	
Precipitation (mm)	2.37	5.96	
Maximum temperature (°C)	11.51	11.73	
Minimum temperature (°C)	1.86	10.80	
Mean temperature (°C)	6.70	11.09	

Panel C – Variation Explained by Fixed Effects and Weather

Dependent variable	R-squared
Daily average NO_X concentration	0.47
Daily average CO concentration	0.65
Hourly $PM_{2.5}$ concentration	0.41

Sources: Air pollution data are obtained from Canada's National Air Pollution Surveillance Program (NAPS). We obtain data on transit strikes from Employment and Social Development Canada's Workplace Information Division. Weather data came from the Environment Canada.

Panel C regresses the dependent variable on NAPS-year, month-day and hour fixed effects as well as the full suite of weather controls as described in equation (2). Substantial residual variation remains for NO_X , $PM_{2.5}$ and CO.

		NOX			CO			$\mathrm{PM}_{2.5}$	
	(1)	(2)	(3)	(4)	(5)	(9)	(2)	(8)	(6)
Transit Strike	-3.771**	-3.906**	-3.988*	0.0180	0.0129	0.0371	-0.841	-0.832	-0.586
	[1.695]	[1.685]	[2.108]	[0.0673]	[0.0668]	[0.109]	[0.715]	[0.729]	[0.506]
Observations	109,613	109,613	109,613	160,352	160,352	160,352	46,734	46,734	46,734
Weather controls	>	>	>	>	>	>	>	>	>
Date fixed effects	>	I	I	>	I	I	>	I	I
NAPS-id fixed effects	I	>	>	I	>	>	I	>	>
NAPS-year fixed effects	>	>	ı	>	>	I	>	>	I
Year-month fixed effects	ı	I	>	ı	ı	>	ı	I	>
Month-day fixed effects	ı	>	ı	ı	>	ı	ı	>	ı
Notes: Dependent variable is d imum temperature, precipitati standard errors clustered by na	aily polluta on and quac ps-id. * sigr	nt concentra lratic precip iffcant at 10	ations. Wea aitation. Al 1% ** signif	ther covaria l weather cc icant at 5%	tes include wariates are *** significa	temperature daily aver: .nt at 1%.	e, quadrati age. Value	ic tempera s in paren	ture, min- theses are

Strikes
Transit
due to
Concentrations
Pollutant
Daily
Change in
Table 4:

		NO_{X}			CO			$\mathrm{PM}_{2.5}$	
	5 miles	10 miles	Close to	5 miles	10 miles	Close to	5 miles	10 miles	Close to
	w. avg.		roads	w. avg.		roads	w. avg.		roads
	(1)	(2)	(3)	(4)	(5)	(9)	(2)	(8)	(6)
Transit Strike	-3.655**	-3.910^{**}	-3.574**	0.0308	0.0366	0.0711	-0.810	-0.763	-0.229
	[1.717]	[1.667]	[1.715]	[0.0554]	[0.0544]	[0.102]	[0.635]	[0.637]	[0.655]
Observations	109,613	111,515	99,420	160,352	162,512	149,987	46,734	47,189	39,179
Weather controls	>	>	>	>	>	>	>	>	>
NAPS-year fixed effects	>	>	>	>	>	>	>	>	>
Date fixed effects	>	>	>	>	>	>	>	>	>

Table 5:	Change in Daily Average	Pollution	Concentrations due Transit Strike	s: Alternative Pollution	Monitoring
Stations					

temperature, precipitation and quadratic precipitation. All weather covariates are daily average. Values in parentheses are standard errors clustered by naps-id. * significant at 10% ** significant at 5% *** significant at 1%.

	(1)	(2)	(3)
	NO_{X}	CO	$\mathrm{PM}_{2.5}$
Transit strike	-7.152^{*}	0.126	-2.265
	[3.969]	[0.128]	[2.058]
Observations	109,613	160,352	47,920
Weather controls	\checkmark	\checkmark	1
NAPS-year fixed effects	\checkmark	\checkmark	1
Date fixed effects	\checkmark	\checkmark	\checkmark

Table 6: Change in Maximum Daily Pollutant Concentrations due to Transit Strikes

The dependent variable is maximum daily concentration of NO_X , CO and $PM_{2.5}$. Weather covariates include temperature, quadratic temperature, minimum temperature, precipitation and quadratic precipitation. All weather covariates are daily average. Values in parentheses are standard errors clustered by NAPS monitors. * significant at 10% ** significant at 5% *** significant at 1%.

		Before			After	
	(1)	(2)	(3)	(4)	(5)	(6)
	NO_{X}	CO	$\mathrm{PM}_{2.5}$	NO_{X}	CO	$\mathrm{PM}_{2.5}$
Transit strike	-0.310	0.041	-3.699*	-10.140*	-0.056*	0.163
	[1.548]	[0.045]	[0.414]	[2.021]	[0.023]	[0.461]
Observations	63,305	113,730	4,177	46,308	46,622	38,389
Weather controls	1	\checkmark	1	\checkmark	1	1
Naps-year fixed effects	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark
Date fixed effects	1	1	1	1	1	1

Table 7: Change in Average Daily Pollutant Concentrations due to Transit StrikesBefore and After 2000

Notes: Dependent variable is daily pollutant concentrations. Weather covariates include temperature, quadratic temperature, minimum temperature, precipitation and quadratic precipitation. All weather covariates are daily average. Regressions also control for public holiday and day of week fixed effects. Values in parentheses are standard errors clustered by naps-id. * significant at 10% ** significant at 5% *** significant at 1%.

Table	e 8: Ch	ange in	Daily A	Average	Pollution	Concentra-
tions	Using	Time S	hifted I	Placebo	Strikes	

	(1)	(2)	(3)
	NO_{X}	CO	$\mathrm{PM}_{2.5}$
Transit strike	-1.121	0.0347	0.294
	[1.055]	[0.0304]	[0.261]
Observations	$116,\!053$	$167,\!077$	$76,\!056$
Weather controls	\checkmark	\checkmark	\checkmark
NAPS fixed effects	\checkmark	\checkmark	\checkmark
Year-month fixed effects	\checkmark	\checkmark	1

The dependent variable is daily average pollutant concentration of NO_X, CO and PM_{2.5}. Weather covariates include temperature, quadratic temperature, minimum temperature, precipitation and quadratic precipitation. All weather covariates are daily average. Values in parentheses are standard errors clustered by NAPS monitors. * significant at 10% ** significant at 5% *** significant at 1%.