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THE QUALITY AND EFFICIENCY OF PUBLIC AND PRIVATE FIRMS: EVIDENCE FROM AMBULANCE SERVICES*

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Abstract

Economic theory predicts that outsourcing public services to private firms reduces costs, but the effect on quality is ambiguous. We explore quality differences between publicly and privately owned ambulances in Stockholm County Sweden, a setting where patients are as good as randomly assigned to ambulances with different ownership status. We find that private ambulances reduce costs and perform better on contracted measures such as response time, but perform worse on noncontracted measures such as mortality. In fact, a patient has a 1.4 percent higher risk of death within 3 years if a private ambulance is dispatched (in aggregate, 420 more deaths each year). We also present evidence of the mechanism at work, suggesting that private firms cut costs at the expense of ambulance staff quality.

JEL Codes: P48, H44, I11, D22, D44, L33.

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I. Introduction

Whether the private sector can provide public services more efficiently than the public is a central issue in economics. This is an important question because outsourcing to private providers is a common way for governments to supply goods and services to their citizens. Across OECD countries, 3 percent of GDP on average is used for welfare services that are contracted out to private providers (OECD, 2019).

From a theoretical perspective, private providers have more high-powered incentives than public providers, and therefore will produce welfare services at relatively lower cost. By implication, private providers also have incentives to provide more of such quality components that are verifiable and therefore contractable. However, the canonical literature also highlights that private providers' incentives to cut costs can be too strong, with an adverse effect on quality when it is non-verifiable (Hart and Moore, 1990; Hart, Shleifer, and Vishny, 1997). Reducing costs at the expense of quality is more likely to occur when innovation pressure is low, competition is weak, consumer choice is inefficient, and reputational mechanisms are weak (Shleifer, 1998).

Credible empirical evidence of adverse effects on quality due to outsourcing is scant and even less is known about the magnitude of any quality reduction in relation to saved costs.[1] The evidence on outsourcing in healthcare is concentrated in nursing home markets and is mixed (Barron and West, 2017; Bergman et al., 2016; Chan, Card, and Taylor, 2021; Duggan, Gruber, and Vabson, 2018; Wübker and Wuckel, 2019).[2] The limited number of papers available reflects the inherent problems of self-selection that usually occur (patients selecting providers or vice versa) and the lack of good measures of quality. With self-selection, any differences could reflect patient characteristics rather than the quality of the service.

This paper furthers the literature by providing a credible empirical evaluation of the performance of public and private for-profit providers in an acute healthcare environment. The efficiency and quality of emergency care is of economic importance since aggregate spending on emergency care could be as high as 10 percent of national health expenditures (Lee, Schuur, and Zink, 2013). Moreover, analyzing the effects of outsourcing is also important because service quality affects essential outcomes such as health and ultimately mortality.

[1] For evidence on outsourcing, see Szymanski and Wilkins (1993), Szymanski (1996) for garbage collection; Bales et al. (2005), Duwe and Clark (2013), Powers, Kaukinen, and Jeanis (2017), Spivak and Sharp (2008) for prisons; and Bayer and Pozen (2005), Armstrong and MacKenzie (2003) for residential youth care. The few experimental studies that examine the effects of privatization or outsourcing in areas such as job placement or vocational rehabilitation point to very small, if any, effects (Behaghel, Crepon, and Gurgand, 2014; Bennmarker, Grönqvist, and Öckert, 2013; Laun and Thoursie, 2014).

[2] A pilot study was conducted by Jansson and Castwall (2017) using one year of our data and the time stamp outcomes (e.g., time to patient) in a bachelor's thesis developed under the supervision of Tyrefors.

To overcome the problem of self-selection, we use ambulance services in Stockholm County in Sweden as a laboratory to answer questions regarding outsourcing in healthcare. From an evaluation point of view, the setting has several important features. After auctions based on competitive tendering, private ambulance firms were granted 5-year contracts at a fixed annual reimbursement to operate ambulance services side by side with the public provider.[3] After the auctions, there was no further entry or exit within the 5-year contract period. In contrast to most of the previous studies, the patients can neither choose provider nor can the providers choose patients, and provider type is therefore independent of patient characteristics. Dispatch operators assign an ambulance to each patient by considering the distance to the patient and alternative use of the unit, but without regard for ownership status. According to their guidelines, the nearest ambulance should be assigned; however, to maintain readiness for emergencies, exceptions can be made for less severely injured patients. As the ambulances that we study have the same capacity to handle different health emergencies, dispatch operators have no incentives to systematically discriminate between providers.[4]

Our first set of results relates to the firm-specific ambulance outcomes of each patient serviced.[5] These outcomes are explicitly contracted for and well documented, with fines ultimately levied if inferior performance is observed. For the salient contracted outcomes, we find that private firms are more efficient. Private firms were 8 percent faster in responding to a dispatch and 7 percent faster in reaching the patient. Since firms were compensated at a fixed rate, these results were not generated by incentives to take up more assignments.[6] We interpret these findings as private firms being more innovative than public for observable and contracted outcomes.

Our main noncontracted quality outcome is mortality. In our second set of results, we find that private ambulances cause increased mortality. Mortality was higher already from the first day of service and remained higher up to three years later if a private ambulance was dispatched. We estimate an effect of a 0.42 percentage points (pp) increase in mortality for privately serviced patients, which amounts to a 1.4 percent higher risk of dying within three years of service from a baseline mortality of 31 percent. This means that, in Stockholm for

[3] Retaining some in-house provision is a common arrangement in practice as discussed in Andersson, Jordahl, and Josephson (2019).

[4] Although our setting is advantageous from an evaluation point of view, it may not be informative without further assumptions about private provision with *ex ante* competition, where consumers can assess the quality or markets are competitive, as discussed by Hart, Shleifer, and Vishny (1997).

[5] By serviced we mean that an ambulance was dispatched and that the ambulance staff met with the patient at the site. Being serviced may or may not lead to a patient being conveyed to hospital.

[6] During the first three years of the sample, the contracts included a very small variable component based on historical patient flows. However, the results are not sensitive to excluding these years.

any given year of the contract period, approximately 420 additional patients died within 3 years because a private ambulance was dispatched. This figure is approximately 50 percent higher than the total number of traffic deaths in Sweden in a single year. Our calculations further suggest that the cost of private ambulances measured in terms of the value of lost quality-adjusted life years (QALYs) is substantial. A conservative estimate puts the loss at 25 percent of the total cost of the ambulance service in Stockholm County and considerably exceeds the cost savings from outsourcing. Considering the two sets of results together, our findings provide strong support for the predictions of Hart, Shleifer, and Vishny (1997).

To understand the mechanisms behind the mortality difference, we analyze outcomes describing how ambulance crews serve their patients. When arriving at the patient, the staff must first assess the medical condition of each patient. This assessment starts with a thorough interview with the patient (and/or bystander) to assess their medical history and current symptoms, followed by diagnosing the patient, assessing the overall severity of their condition, and deciding whether to convey the patient to hospital. We find that private ambulances diagnosed more generic conditions, assessed fewer patients as having cardiovascular diseases (CVDs), and assessed patients to be overall less severely sick or injured, although the baseline characteristics were *ex ante* balanced across provider types. These findings are striking, given that patients served by private ambulances had higher mortality in both the short and the long term. However, for conditions that are difficult to misdiagnose, such as cardiac arrest, there are no differences across provider type. Consistent with these assessments, private ambulances left 32 percent more patients at home (a 3.2 pp increase compared to an average of 10 percent for public ambulances).

To gain a better understanding of the importance of the conveyance decision, we analyze hospital admission data for each ambulance dispatch. If a patient is conveyed, the admission decision at a hospital is based on a new medical assessment. The patients who had a private ambulance dispatched had 1.2 pp *fewer* hospital admissions and, consistent with underdiagnosing by the ambulance crew, fewer patients were admitted with a CVD as the primary intake diagnosis.

That private providers leave more patients at home cannot be explained by financial incentives, because ambulance firms are not paid per assignment. Instead, we argue that our results can be explained by differences in staffing policies that enable private providers to hold costs down. As a result, private firms attract and retain on average lower-quality staff than the public provider. There is evidence of longer working hours, extensive use of overtime and temporary staff, and less on-the-job training. Additional information from matched employer-employee data at the county level shows that private firms have employees who change workplaces more often and have lower cognitive skills, although some of the differences lack statistical power. Intriguingly, annual wage income is higher for private ambulance staff. However, when also accounting for longer working hours, the evidence points to an hourly wage disadvantage.

Our confidence that we have estimated causal effects is supported by a credible study design. Although ambulances are assigned without concern for ownership status, the identification of causal effects in this setting relies on the probability of being serviced by a private ambulance being unrelated to a patient's health status. However, this assumption can be undermined if the location from which a patient calls affects his or her probability of being serviced by a private ambulance. Patients living close to a private ambulance station—hence having a higher probability of private ambulance service—could differ from those residing close to a public station.

To estimate the causal effects of ambulance providers, we employ a fixed-effects strategy, exploiting narrowly defined geographical fixed effects. Using the GPS coordinates of each patient location at the time of the call, we create geographical fixed effects of a block-level size (approximately 190 by 140 meters) to ensure that the treatment probability is essentially constant within each grid and unrelated to patient's characteristics. Thus, we compare patients who are experiencing medical emergencies and are calling from the same residential block. Accordingly, ambulance assignment between private and public providers is determined stochastically by ambulance availability and ambulance distance to the patient at the time of the call.

This interpretation of our results is verified by a test of balance and correspondence of the criteria with the assignment center. We find no evidence of any systematic relationship between the assignment of the type of provider and patient characteristics.[7] We also show that the estimated effects are very close to those of our main specification under a series of regression-model specifications and context-relevant exclusions of data. For example, we find similar results when considering districts mainly served by either private or public ambulances, suggesting that the mechanism producing our findings is not specific to geographical differences in the locations of private and public ambulance stations.

Our findings contribute to the literature on outsourcing and quality, recently surveyed in Andersson, Jordahl, and Josephson (2019), and support their conclusion that the ability to contract quality is paramount to maintaining the quality of public services. Our paper adds new evidence to the small literature on the quality of private provision in healthcare. Bergman et al. (2016) show that private nursing homes in Sweden had lower mortality than public nursing homes. In Germany, Wübker and Wuckel (2019) show that for common diag-

[7] Importantly, our results do not hinge on a specific set of fixed effects but are consistent across a wide variety of different specifications.

noses, for-profit hospitals performed no worse—or even better—than public hospitals. One main difference from these studies is that our results emerge in a context where consumers cannot choose their provider, which could explain the difference.

Of further relevance to the present study is the literature in economics that has studied staff productivity, which can be crucially important in healthcare. Bartel et al. (2014) find that nurses' education and on-the-unit experience increased productivity in hospital environments. Our findings suggest that important health outcomes can also be susceptible to healthcare staff quality. Gruber and Kleiner (2012) find that during the nurses' strikes in New York in 1984 to 2004, in-hospital mortality increased by 18 percent, even when hospitals engaged temporary staff. Similarly, Gruber, Hoe, and Stoye (2018) study physician practices in emergency departments (EDs) when a new regulation imposed a strict ceiling on waiting time before seeing a physician. As patients were cared for sooner, more patients were admitted to a hospital ward, and mortality decreased by 14 percent. Our findings confirm the susceptibility of patients seeking emergency care to small changes in staff practices.[8]

In markets where for-profit firms are at risk of neglecting quality, a possible solution is to incentivize not-for-profit firms to produce services (Bennett and Iossa, 2009). Not-for-profit private firms have the potential to credibly commit to noncontracted soft incentives while maintaining intrinsic motivation and keeping costs down (Francois, 2003; Glaeser and Shleifer, 2001). Several studies on nursing homes document that private for-profit firms perform worse than private not-for-profit firms (Grabowski et al., 2013; Tanuseputro et al., 2015). The ambulance market could be a suitable context for not-for-profit firms if public in-house production is inadequate.[9]

The remainder of the paper is organized as follows. Section II addresses the background and institutional details. In Section III, we describe the methodology and empirical design. In Section IV, the results are presented, and in Section V, we perform further analyses on mechanisms, heterogeneity, and robustness. In Section VI, we conclude the paper. All appendix material is found in the Online Appendix.

[8]Other evidence on the importance of healthcare resources is provided in Doyle (2011) and Doyle et al. (2015). The consequences of emergency medical services (EMS) staff fatigue are explored in Patterson et al. (2012). Rivard et al. (2020) consider how multiple jobs and workload affect EMS employees' job satisfaction, and Rogers et al. (2004) analyze the relationship between long working hours and medical errors. For descriptive evidence on mortality among non-conveyed ambulance patients, see Lederman et al. (2020) and Ebben et al. (2017). Regarding mortality, several studies document the importance of the early detection of, treatment of, and adherence to treatment for CVDs (Korhonen et al., 2017; Lindahl et al., 2017; Orchard et al., 2018; Rothwell et al., 2007).

[9]However, our results do not relate to the performance of not-for-profit firms, as there are no such firms competing for ambulance contracts in Stockholm. Moreover, our results may not be externally valid in other contexts where governmental quality is low.

II. Background

II.A. The Ambulance Market in Stockholm

Stockholm County is the largest healthcare region in Sweden, with 2.3 million inhabitants in 2017. The ambulance service is completely financed by the public sector (through county income taxes) but with for-profit firms competing for contracts in lowest bid auctions for five-year contracts.[10] The total cost of ambulance ground transports was approximately 36 million EUR in 2010, when 55 ambulances took on 145,000 assignments (HSF, 2011). Reflecting the increasing population of Stockholm, the number of ambulances increased from 2010 through supplementary contracts. In 2016, 73 ambulances responded to 220,000 dispatches at a total cost of 52 million EUR (HSF, 2018).

Already in the 1980s, there was a change in many OECD countries towards outsourcing of welfare services, often referred to as New Public Management (Hood, 1995), to lower the costs. In Sweden, the 1990s have been described as "the decade of markets" for the welfare sector (Svedberg Nilsson, 2000). At that time, the Swedish Competition Authority pointed out that competition in the ambulance sector had the potential to lower costs by approximately 20 percent (SPK, 1991). The new Swedish Local Government Act of 1991 was essential for this process as it opened up the welfare sector for competition between for-profit private and public providers, through competitive tendering or authorization with customer choice (Hartman, 2011).

After the new law was ratified, Stockholm County decided that ambulance services were to be exposed to competition. In 1993, the previously in-house unit was transformed into a public company, and Stockholm County was divided into 7 commercial sectors for which firms engaged in competitive tendering. This system remained until 2005, when the Health and Medical Care Board (Hälso- och sjukvårdsvårdsförvaltningen) decided that the public provider should be given given exclusive rights for two sectors located in central and western Stockholm. The decision was taken without any documented explanation. The County auditors concluded that procurement was made in good order and was commercially sound, but criticized the lack of explanation for why two sectors were exempted from tendering (SLL, 2005b).

Private firms have since 2005 competed for five sectors, with each firm being allowed to operate in at most three of them (AISAB, 2020). In 2009, in addition to the public provider, three private firms operated in the sectors. One auction was held during our period of study (2009-2016) in 2011. During this auction, one firm lost its contract, meaning that only two

[10] The contracts last for five years, with the additional possibility of an extension of up to two years. Auctions for ground-based ambulances were held in 2005, 2011, and 2017.

private firms remained. The two remaining private firms, together with the public firm, are still the sole service providers. (Online Appendix Figure A.1 shows the locations of the stations during this period).

The auctions before 2011 had specified conditions. A fine could be levied if the response times after dispatch calls were too slow. The ambulance crews were to be ready to depart within 90 seconds after a dispatch for an emergency (priority 1) and within 180 seconds for other assignments (priority 2 or 3). Fines could also be levied if the contracted ambulances were not operational as required (on repair without a replacement or without staff) or if staffing requirements were not fulfilled (at least one Master's degree specialist nurse in the ambulance crew). The transport time to each patient was carefully monitored but not tied to a monetary fine. Firms were compensated with a fixed component and a small variable component based on historical patient flows. The fixed amount, allowing firms to maintain vehicles, staff, and garages, was slightly adjusted on a yearly basis according to changes in the number of dispatches compared with the previous year (SLL, 2005a).

From 2011, the County of Stockholm started to weight quality as 25 percent of the bid, but the same structure was maintained with respect to fines. The variable compensation was removed, and requirements to gradually increase the use of renewable vehicle fuels were tied to fines. The maximum fine that firms could be required to pay was 3 percent of the contract value (Landstingsrevisorerna, 2013). Fines were not conditioned on health outcomes, mortality, or any other direct quality measure. The contracts also specified the required number of ambulances in each sector, their equipment, and their service time availability. Additionally, since 2008, together with at least one trained paramedic, a registered nurse with a Master's degree in nursing was required to be present in an emergency ambulance.[11]

Table I describes the annual contracted service hours and the outcome of the auction in 2011, i.e., the annual compensation. The private firms were contracted for 274,248 hours, comprising 67 percent of total hours. They received annual compensation of approximately 25.7 million EUR in 2012 vs. 15.9 million EUR for the public provider. The total annual

[11]The contracts included other types of units. From 2009 to 2012, these consisted in part of several transport ambulances staffed only by paramedics and mainly responding to priority 3 dispatches for which medical treatments were not required. There were also two emergency cars in Stockholm that included a nurse with a specialist degree in anesthesiology. These were not able to transport patients but were allowed to assist an ambulance when the patient was severely ill. Furthermore, two helicopters were contracted, of which one was available during the summer months (HSF, 2011). Under the new contract from 2012, the ambulance system changed somewhat. An emergency car with a specialist physician onboard was instituted. The two emergency cars that were already operational were upgraded to have patient transportation capacity, meaning that they could take on emergencies alone if required and transport patients to hospitals. The staffing of these vehicles was unchanged, and they were still intended to be used in medical emergencies and in support of other ambulance units. From 2012, helicopters were supplied by a separate private firm that was not operating ground transports, whereas emergency ambulance cars were supplied by private firms (HSF, 2018).

bill added up to approximately 41.6 million EUR. The average cost per hour of service was 116.7 EUR for the public provider and 24 percent lower for the private firms at 93.9 EUR. Thus, if the public provider would have been the only producer of all service hours at the public rate of 116.7 EUR per hour, then the total bill would add up to 47.9 million EUR, an increase of approximately 6.2 million EUR annually.

[Table 1 about here.]

II.B. The Geography of Ambulance Dispatch and Transport in Stockholm

The ambulance dispatch firm in Stockholm, SOS Alarm AB, is instructed to achieve two main targets. First, the most severely injured patients should be prioritized. Second, patients should be matched to ambulances with as little waiting time as possible while still maintaining sufficient readiness for other medical emergencies (SOSAAB, 2020).

When calling the emergency number 112, the caller is connected to an emergency operator.[12] Based on the need for assistance from the police force, fire brigades or ambulance services, the caller is connected to a specialist to further assess the emergency. Once the specialist has made an assessment of the caller's urgency (priority), an ambulance work description is sent out, including the priority of the emergency, patient characteristics, characteristics of the injury, and patient location. A dispatch operator then takes the job and assigns the patient to an ambulance according to the main objectives. If the patient's condition is sufficiently severe, several units can be assigned to the same patient.[13] According to SOS Alarm AB, the assignment should immediately be directed to the closest ambulance if the patient's condition is life-threatening (priority 1) or potentially life-threatening (priority 2). The assignment can be placed on hold if no suitable units are available and the patient's condition is not affected by a time delay (priority 3). In reality, cases with priority 2 or 3 can be placed on hold to facilitate readiness for emergencies (RiR, 2012).

Several ambulance stations exist within each firm-specific sector. These stations have one or more ambulances and are planned to primarily serve the district around the station. However, the dispatch operator is not restricted to assign ambulances based on the district's boundaries. If the local ambulance is unavailable in its district, e.g., if it is occupied by another patient or relatively far from the patient, another ambulance is called, based on proximity. An ambulance can be dispatched to any location in the county, although very

[12] Information regarding SOS Alarm AB and how it operates has primarily been collected through personal contacts with employees of the firm.

[13] Multiple-unit dispatches are rare (4 percent in the data). We exclude these in the robustness analysis (Figure IV, row (5)) and use multiple-ambulance dispatches as a predetermined characteristic in our balance test.

long transport times to patients are rare. In essence, whether a patient is picked up by local ambulance or by one from another station depends on the relative distance and availability of that ambulance compared with others nearby.

Importantly, patients residing in the same neighborhood are taken to the same assigned hospital. Exceptions can be made if a patient is currently under treatment at a different hospital or if specialist care elsewhere is required. However, the ambulance crew does not have this discretion. Therefore, the distance to the hospital or hospital resources are not a factor that can explain our results, in contrast to other studies, e.g., Doyle, Graves, and Gruber (2017).

III. Empirical Design and Data

III.A. Empirical Design

Estimating the causal effects of outsourcing public health services to private firms on quality outcomes is inherently challenging. The main challenge comes from patients sorting themselves into different health providers based on e.g., income, education, personal contacts, and residence. Furthermore, patients' health may determine by whom and at what location they receive care.

The ambulance services that we study provide some clear advantages in this regard. Patients cannot sort into either a private or a public ambulance. The dispatch operator assigns the patient to an ambulance based on criteria that the patients themselves cannot affect. For severe cases (priority 1), distance (or time to patient) is the sole allocation criterion. In general, ambulances do not differ in terms of resources. All ambulances have the same equipment and the staff the same formal education.[14]

However, even if patients cannot choose ambulance providers, they choose where to live, and providers operate more frequently in certain areas. The public firm mainly services the inner city and a few nearby districts. The private firms mainly service the suburbs and distant cities, villages, and rural communities in the larger county of Stockholm. These populations differ in many characteristics. Hence, a naive comparison of outcomes by public-private status is likely to yield a biased estimate because of incomparable treatment and control groups. Fortunately, ambulance assignment is not bound by the district borders. Thus, almost all patients have a nonzero probability of being serviced by a private ambulance, regardless of residency.

To identify the causal effects of the ownership status of ambulances, we rely on the

[14]Before 2012, only ambulances operating around the clock were equipped with electrocardiogram (ECG) monitoring capabilities, but these ambulances were not exclusive to any particular provider.

cross-district movements of ambulances. Several different situations give rise to cross-border movements. First, a local ambulance can already be servicing a patient and thus be unavailable for a new assignment. Second, an ambulance from a different district might be closer to the patient. Third, maintaining readiness for future emergencies might require assigning a different unit than the district-specific ambulance. These situations are unpredictable and unrelated to patient health given the priority set by the emergency operator and the location of the patient.

However, to exploit this randomness in ambulance assignment, we need to hold constant the probability of being assigned a private ambulance. Being assigned a private ambulance is related to the patient's location and his or her distance to the nearest ambulance stations. To hold constant the probability of private service, we control for geographical fixed effects at a local level. We construct a grid of squares covering the entire County of Stockholm and assign the patients to the grid based on information on each patient's location with GPS coordinates. Empirically, we include fixed effects for each of the grid cells in our regression models to hold constant the probability of treatment (Krueger, 1999).

Using these narrow fixed effects, the identification approach compares patients who ask for an ambulance in close proximity to each other, i.e., within a particular grid cell. For example, our baseline grid size is about 190x130 square meters, resulting in approximately 16,000 effective area fixed effects with variation in the identity of the ambulance provider type.[15] Normally, the chosen grid size reflects a tradeoff between bias and variance if the treatment effect is homogenous. Thus, if the size is small, patients are more similar, and less bias exists. On the other hand, the variance is also larger if the size is small as there is less variation in the treatment. However, a heterogeneous treatment effect complicates the appropriate choice of size. For example, if the treatment status varies only within some cells, then using a smaller size might induce more bias ("selection into identification"), as discussed by Miller, Shenhav, and Grosz (2019). Therefore, we also show that our results are not sensitive to varying the size of the grid cells in the Online Appendix (Figure C.1).

In addition to geographical fixed effects (α_g), we include not only year but also month fixed effects in our main specifications. Time fixed effects might be important because changes in the treatment probabilities over time could result from changes in supply and demand (e.g., introducing new ambulances to different ambulance stations). We consider more flexible fixed effects in the robustness section but refrain from doing so in our main specification, as overspecifying a model with fixed effects can have adverse effects (Miller,

[15]Theoretically, we can estimate up to 720,000 fixed effects. However, many of these grids cells are not populated, or contain only a single observation. Our baseline model estimates approximately 32,000 fixed effects, whereas the number of grid cells with private-public common support is smaller at approximately 16,000.

Shenhav, and Grosz, 2019).[16] We also include indicators for how urgent the dispatch operator determines the assignment to be, since transport urgency is part of the observable treatment allocation mechanism (Priority_{igt}). Including these control variables, our main model to be estimated by OLS is:

$$\text{Outcome}_{igt} = \alpha_g + \beta * \text{Private}_{igt} + \text{Year}_t + \text{Month}_t + \text{Priority}_{igt} + \epsilon_{igt}. \tag{1}$$

In equation (1), the outcome of individual i in grid cell g at time t is causally related to the ownership status of the ambulance servicing the patient (Private_{igt}) through the coefficient to be estimated β. The error term ϵ_{igt} captures all other factors affecting the outcome. The aim of this analysis is to mimic a random allocation of ambulances to patients, and a testable implication is that we expect to see similar characteristics among patients in the same grid cell across provider type.

To test whether patients serviced by private or public providers are similar, we use predetermined variables on the left-hand side in Equation (1) and estimate the coefficients on the variable Private (the treatment). The estimated coefficients are now the differences in these characteristics between patients serviced by a public and a private ambulance conditional on the control variables included. The predetermined variables that we consider are either measured before the study period begins in 2007-2008 (hospitalizations and outpatient visits) or at the time of ambulance dispatch (age, sex, multiple units, previous ambulance transport, and residence in a nursing home). To further show that our design solves inherent imbalances between patients serviced by private and public ambulances, we also display correlations between the predetermined variables and the Private dummy, i.e., the results from bivariate regressions.

We follow Abadie et al. (2017) with respect to the standard errors. On the one hand, our patients are as good as randomly assigned to treatment (resembling a randomized control trial); therefore there is no general need for clustering. On the other hand, our design is based on comparing patients within small but fixed geographical grids. Since ambulance stations are fixed in space, it is not unreasonable that there is some positive—but not perfect—correlation of treatment assignment within grids. Abadie et al. (2017) show that if there are also heterogeneous treatment effects in this type of setting, a clustering adjustment can be motivated. Since the latter cannot be ruled out, we choose to be conservative and cluster our standard errors at the fixed effects level, although we acknowledge that our standard errors

[16] In Figure IV we present results from regressions using finer definitions of the time fixed effects. Ultimately, we use unique hour fixed effects (year*month*week*day*hour). To be able to efficiently estimate a large set of fixed effects, we use the STATA command *reghdfe* (Correia, 2014).

are too large. However, our choice of the level of clustering turns out not to be important for our results. The Online Appendix shows the sensitivity of our standard errors when clustering on different grid sizes (Figure C.1), using unclustered standard errors, clustering at the patient levels (patients are sometimes observed multiple times in our sample), and using randomization inference (Figure C.2).

III.B. Data and Variables

Our data set contains more than 1.1 million ambulance assignments for close to 500,000 unique patients, where almost 60 percent of the assignments are provided by private firms. The data come from the VAL database, which originates from the County of Stockholm. The county is responsible for all publicly financed healthcare in greater Stockholm and maintains health registries for research, evaluation and monitoring of care. We use the ambulance registry and pool all ambulance dispatches between 2009 and 2016. An ambulance assignment—an observation—is registered in the database only if a patient was present when the ambulance arrived. We merge several other registries from the same database into the ambulance data, including the registries for inpatient care, outpatient visits, and mortality. Finally, we are able to merge GPS position data from the dispatch services (SOS Alarm AB), providing us with each patient's location at the time of the call. We can uniquely merge these data to each ambulance assignment using a unique dispatch ID number.

The geographical position information that we have for each patient is used to generate the grid cell fixed effects. To do this, we first transform the GPS data (latitude/longitude) into Cartesian coordinates by using the STATA command *geo2xy* (Picard and Stepner, 2015). We then use the two positions that include the County of Stockholm (northwest and southeast) and generate the grid as X times X equally sized rectangles between these points by grouping observations in each cell. We do this for several values of X, but our baseline specification includes 850x850 grid cells.

A unique feature of this study is that we can observe and evaluate contracted and noncontracted outcomes, which is important because contract incompleteness is key in the model of Hart, Shleifer, and Vishny (1997). The contracted or monitored variables are automatically reported time stamps in the data describing the time intervals of the ambulance dispatch during all stages, i.e., the response time to a dispatch, time to patient, time at patient, time to hospital, and time at hospital.[17] Response times and time to patient are parameters under contract and are associated with fines or monitored in follow-up meetings. The main noncontracted outcome that we observe is mortality. Since we have the date of death for all ambulance patients up to 2019, we create several variables describing whether the patient

[17]See the Online Appendix, Section F, for more information on the time stamps.

died within a certain time—from one day up to three years—after the ambulance dispatch. This type of health outcome should ideally be contracted for in this setting to provide strong incentives to uphold quality. However, this would require large amounts of data, credible evaluation methods, and measures that are robust to provider moral hazards (Gupta, 2017).

Although we present our main results on mortality for all time frames that we consider, we focus on the 3-year mortality throughout the paper. This choice is not motivated by a particular expected health mechanism, but by the variety of conditions that ambulance crews face on a daily basis. Trauma and medical emergencies (such as acute cardiovascular conditions, car accidents and drug overdoses) have a higher likelihood of mortality close in time to the emergency call. Geriatric conditions or milder symptoms, which are common in the data, are associated with the elderly, who have a higher likelihood of mortality but with a longer delay. Three-year mortality provides a more complete measure of quality in outsourcing and enables the consideration of all kinds of conditions and patients. Not evaluating even longer mortality measures is motivated by data availability and by the fact that the treatment effect in the very long run must tend toward zero.

To focus attention on emergency ambulances that are generally comparable in terms of staff and equipment requirements, we exclude transport ambulances (which were phased out from 2009 to 2012), intensive care ambulances (only one unit that was publicly owned), and a few other rare ambulance types that are directed toward particular patients (including helicopters, which are strictly privately owned). Since the vast majority of units during this time are regular emergency ambulances, this excludes 38,500 observations. Our final sample consists of at most 1,075,984 observations. For further information on the data, see the Online Appendix, Section F.

IV. Results and Discussion

IV.A. The Ambulance-Serviced Population

Table B.1 in the Online Appendix shows the descriptive statistics for the predetermined variables of the data used in the analysis. 45 percent of the observations in the data include patients with a previous ambulance contact within one year, suggesting that the average serviced patient is prone to acute illness or has a severe chronic health condition. This can be explained by the ambulance-serviced population being old, with the average patient being 62 years old and 7 percent of patients residing in a nursing home. Many patients in this population were also chronically sick: in 2007-2008, 10 percent had a diabetes diagnosis and 7 percent had a chronic obstructive pulmonary disease (COPD) diagnosis. Table B.2 in the Online Appendix describes the treatment, controls, and outcomes variables. Ambulance-serviced patients have close to a 31 percent three-year mortality rate and a 6 percent one-month mortality rate. Thus, ambulance-serviced patients are often old, sick, and frail. Minor changes in their care or treatment could thereby have vast implications for their health and survival.

IV.B. Balance

As shown in Figure A.1 in the Online Appendix the ambulance stations are not randomly located, and the average patient serviced by a private ambulance could be different from the average person serviced by a public ambulance. However, we argue that any imbalance across groups reflects geographical differences in the probability of being serviced by a private ambulance. If this is the case, any observed differences should vanish if conditioned on fixed effects based on sufficiently small geographical units (grid cells).

To support this argument, Figures I and II show the results from balance tests. In these figures, we use 36 predetermined characteristics as outcomes, including the most common diagnoses we observe in the patient data in 2007-2008.[18] In the left Panel of both figures, we show the results when no grid fixed effects or other controls are included, i.e., the results from a simple bivariate regression. In the right panels of the same figures, we use our design-based approach, the full specification of Equation (1).

From the left Panel of Figure I we conclude that the patients for whom a private ambulance was dispatched are indeed unconditionally different. For example, private ambulance-serviced patients are 0.05 standard deviations younger than public ambulance-serviced patients, amounting to a raw average age difference of almost 1.25 years. Reflecting this age difference, private ambulance-serviced patients seem, on average, to be healthier than public ambulance-serviced patients. They are less likely to live at a nursing home and have fewer healthcare contacts in 2007-2008. Although private ambulance-serviced patients appear unconditionally healthier, they are more often allocated more than one ambulance. Being assigned more than one ambulance, or an additional unit with a specialist competence, is a strong indication that a life-threatening event has taken place.[19] The left Panel of Figure II shows a more complicated scenario, with private ambulance-serviced patients having more lifestyle-related diagnoses (such as diabetes, hypertension and hyperlipidemia) but fewer diagnoses related to substance abuse.

In the right panels of Figures I and II, we re-estimate the same models using our preferred

[18] We create 5 groups by using information from the diagnoses, namely, CVDs, respiratory diseases, psychiatric diseases (including drugs and alcohol), cancer and pain-related diseases, and an indicator variable for having more than one diagnosis in 2007-2008. Thus, these variables are functions of the other predetermined characteristics.

[19] Patients serviced by multiple units had a 15 percent risk of dying within one day of ambulance service.

specifications (adding grid cell, time, and dispatch priority fixed effects). Out of 36 tested hypotheses, only two—the hypotheses regarding whether the patient had any primary care contacts in 2007-2008 and whether they had an anemia diagnosis—are significant at the 5 percent level. The first of these estimates is negative at 0.3 pp and suggests that, if anything, patients serviced by private firms were healthier prior to the dispatch. The second significant estimate is positive and suggests that private ambulance patients are 0.08 pp more likely to have had an anemia diagnosis in 2007-2008. However, since these estimates are very close to zero, marginally significant, and 36 hypotheses are tested, we do not interpret this result as a sign of imbalances, but close to what we would expect from random sampling. The other variables tested are close to zero, insignificant, and—most importantly—provide support for the assumptions underlying our design that, conditional on the fixed effects, ambulance provider assignment is unrelated to patient health. Furthermore, our preferred model explains much of the residual variation in the outcomes, as reflected by meaningful reductions in the standard errors on all estimates. We interpret these findings as strong support for our design's ability to address geographical selection as present in the data.[20]

[Figure 1 about here.]

[Figure 2 about here.]

IV.C. Effects on Contracted Outcomes

We study two outcomes that are perfectly observable and contracted or reviewed: the response time after the dispatch call and the ambulance time to the patient. Again, we present the full specification of Equation (1). In Table II, column (1), we show that private ambulances respond 8 seconds faster—a decrease in the response time of nearly 8 percent. The standard errors in brackets show that this estimate is highly statistically significant with a t-statistic of close to 10. We further find, as reported in column (2), that private firms reach their patients faster. Private firms are 61 seconds (or approximately 8 percent) faster, which is a considerable amount of time given that a time delay is a key factor in the health emergency literature (Jena et al., 2017; Lucchese, 2020). Again, the estimate is highly statistically significant. Thus, the results confirm the predictions in Hart, Shleifer, and Vishny (1997) that private firms are more efficient when evaluating outcomes that are observable and contracted for.

[20] As age could be the potential driver of many of the unconditional health differences, we provide kernel density plots of the age distributions between the public ambulance- and private ambulance-serviced patients (see the Online Appendix, Figure A.2). We show both the unconditional and conditional differences in age distributions between public and private firms. We find that the two estimated distributions are extremely close to one another once we residualize by using our main specification.

[Table 2 about here.]

IV.D. Effects on Noncontracted Outcomes: Mortality

The ultimate quality measure for health services is often mortality. Again, we present the specification of Equation (1), now using mortality as the outcome. Table III, column (1), displays the effect of a private ambulance being dispatched on mortality within 1 day of service. For private ambulance-serviced patients, the mortality within one day is significantly higher (0.1 pp). The effect increases rather monotonically as we increase the time span.[21] That the effect increases over time implies a negative effect of private ambulance service on health, not only for critically ill patients, who have a high probability of dying in connection to the ambulance dispatch, but also for patients with milder symptoms for whom treatment decisions can have lasting effects over time. There is no significant increase when evaluating the difference between 2- and 3-year mortality, consistent with the fact that any treatment effect on mortality for a given sample must start to decrease at some point.

We find the largest absolute effect when evaluating 3-year mortality. The effect size is 0.42 pp, which (at a mean of 31 percent) yields an increase of 1.4 percent. To illustrate the magnitude of this effect, we use the following example. Considering that private firms service approximately 100,000 patients each year, the estimated effect suggests that private ambulance service led to an additional 420 deaths each year (within three years). This number is considerable; for example, traffic accidents in the whole of Sweden cause a total of 200-300 deaths each year. In the Online Appendix, Section E, we calculate the value of lost QALYs based on our estimates. Even under conservative assumptions regarding the number of lives lost due to private service, the total cost is still substantial. Considering our most conservative QALY weight of 0.1, the yearly cost is still 10 million EUR, a quarter of the total cost of ground-based ambulance services in Stockholm in 2012. As previously discussed, outsourcing ambulances in Stockholm could generate cost savings of up to 6.2 million EUR. Even if we use our most conservative assumptions, our calculations suggest that the cost of reduced quality vastly outweighs the cost savings that outsourcing generates. The aim of the next section is to understand the underlying mechanism of why private ambulances underperform in terms of quality in both the short and the long term.

[Table 3 about here.]

[21] See Online Appendix, Figure A.3, for a graphical illustration.

V. Mechanisms and Heterogeneity

The superior performance of private firms on contracted quality measures and their inferior performance on the noncontracted lines up well with the predictions of Hart, Shleifer, and Vishny (1997). In this section, we argue that the results are generated by differences in the firms' personnel policies which affect staff quality and therefore patient health. Although staff quality is regulated with respect to education and basic training, cost-minimizing firms can save on staff expenditures by offering less favorable employment contracts and poorer working conditions, thereby potentially affecting service quality.

We first show that on site diagnosing differs substantially across providers and that this affects the care patients receive. Next we present a heterogeneity analysis that sheds light on the types of patients that drive our main results. Then we discuss evidence of fundamental differences in personnel policies between firms. From matched employer-employee data, we also provide evidence of staff quality differences. Moreover, we relate the magnitude of our effects to comparable interventions that have been studied in the medical literature. Finally, we discuss competing mechanisms based on sorting unrelated to private firms' production choices.

V.A. Immediate Responses

In Table IV, we study the immediate actions taken by ambulance staff when arriving at a patient's location. We know from Figures I and II that patients within a cell are comparable. Thus, differences in assessments are the result of crew behavior.

When arriving at the patient, the staff must first assess the patient's medical condition. A thorough interview with the patient (and/or bystander) to assess the patient's medical history and current symptoms can be combined with several clinical examinations, such as blood pressure, respiratory rate, blood sugar, ECG monitoring, pulse oximetry, and pulmonary auscultation. We lack information on these examinations, but we have access to data on the diagnosis as assessed by the ambulance crew. When entering the diagnosis into the journal system, the staff can choose between 160 preregistered categories. The categories are important, as the diagnosis dictates the actions taken (and not taken) during the assignment. The appropriate actions are described in explicit guidelines for several acute conditions. For example, if the ambulance crew diagnose a patient as having an acute myocardial infarction (AMI), the ambulance guidelines dictate providing an oral anticoagulant, oxygen, and pain relief on demand, administering an ECG, and monitoring vital signs. Moreover, to prepare the emergency room (ER) for ambulance arrival, the information should be provided to the receiving hospital together with the ECG for further assessment by a specialist. Providing a pre-hospital ECG has been associated with a 35 percent lower 30-day mortality compared to not being provided with an ECG among ambulance serviced patients with chest pain (Rawshani et al., 2017). Thus, making correct assessments for critically ill patients is important for the care that a patient receives.

[Table 4 about here.]

Our first result in Table IV, column (1), suggests that private ambulance staff make less-specific assessments. Compared with public ambulance staff, private ambulance staff are 35 percent more likely to use a generic category (such as "general other") to define the patient's condition. The natural follow-up question is what the underassessed diagnoses are. We present four broad categories and one distinct diagnosis that are commonly used and jointly make up about 30 percent of all patient diagnoses. These are CVDs, psychiatric/drugs, respiratory diseases, and gastrointestinal (GI) diseases.[22] From the CVD category, we take out cardiac arrest as a standalone diagnosis that is difficult to misdiagnose for the ambulance crew. Thus, we do not expect any large differences in the assessments for cardiac arrests. The results are presented in Table IV, columns (2)-(6). We find that private ambulance crews diagnose fewer patients as suffering from CVDs, including AMI and stroke, where timely treatment is of the essence. There are no statistically significant differences for the other categories. Reassuringly, in column (6), we do not find any statistically significant difference in diagnosing cardiac arrests.

Although we have shown that private ambulance staff make different assessments regarding their patients' specific conditions, we do not know whether they make different assessments of overall severity. To approach this question, we use the severity classification from 0-7 that has to be reported in the ambulance medical record (where 7 is the most severe). In column (7), using this measure as the outcome, we show the effect of having a private ambulance dispatched. We find that the patients serviced by private firms are reported as less severely ill than the patients serviced by the public provider. Although this difference is not very large (approximately 5 percent of a standard deviation), this finding is intriguing, given the increased mortality risk from a private ambulance dispatch even in the short run. The possibility that private ambulances are somehow matched with more severely ill patients, even if this is at odds with our balance test results, seems implausible.

Finally, the assessment is also linked to the choice whether or not to convey the patient to hospital. As shown in Table IV, column (8), private ambulance crews are more likely to

[22]The psychiatric/drugs category includes all intoxications, including alcohol, and psychiatric diagnoses. CVDs are a combination of cardiac arrests, AMI, fibrillation, heart failure, stroke, and general circulatory complaints. In the respiratory category, we include asthma, COPD, the common flu, respiratory obstructions, and any other respiratory diagnoses. The GI category includes ulcer, pain, ileus, and bleeding from the intestinal tract. For further details, see Online Appendix Table F.4.

leave patients at home, consistent with their severity assessment. In total, 12 percent of all patients are not conveyed (see Online Appendix Table B.2), and our estimated effect suggests that private firms leave 3.2 pp more patients at home than public firms (a 32 percent increase from the public mean). We argue that this is strong support for immediate differences in actions taken upon arrival at a patient's location. Leaving more patients at home could provide a possible explanation for why we find effects on mortality immediately after each dispatch.

Non-conveyance of ambulance serviced patients has been related to under-diagnosing and negative health outcomes. A study from Sweden found that 3-4 percent of patients with a Stroke/TIA (transitient ischemic attack) were not directly transported to a hospital by the ambulance crew (Magnusson et al., 2021). Lederman et al. (2020) studied non-conveyed patients in Stockholm in 2015 and found that among the patients who were 65 years or older—representing nearly half of their adult sample—28 percent visited an ED and 21 percent were hospitalized within 7 days of being left at home. Moreover, 0.4 percent of this older group died within 1 day of non-conveyance, and 1.1 percent died within 7 days. A recent literature review found that 1-day mortality ranged between 0.2 percent and 3.5 percent among non-conveyed EMS serviced patients (Ebben et al., 2017). Given the high mortality among non-conveyed elderly patients, private ambulances not conveying older patients could explain the immediate effects on mortality that we estimate.

To substantiate the importance of non-conveyance for the marginal group of patients that are conveyed only if a public ambulance is dispatched, we investigate the effect of a private ambulance on mortality for conveyed and non-conveyed patients respectively. We decompose the main treatment effect by running two separate regressions when imposing different constraints on the mortality variable. In the first regression, we use an indicator variable as the outcome, taking a value of one if the patient is dead and not conveyed and zero otherwise (i.e., if the patient is alive and not conveyed or conveyed and either dead or alive). In the second regression, the outcome takes a value of one if the patient is dead and conveyed and zero otherwise.

The two mortality outcome variables complement each other, and the resulting estimated effects of private ambulance dispatch sum to our treatment effect because we do not place restrictions on the included sample. If the effect of private ambulance dispatch is generated by non-conveyance, we would expect to find strong results using the first regression but not the second. The results are shown in Online Appendix Table B.8 and are consistent with our interpretation that the mortality effect is primarily driven by patients that are non-conveyed. To better understand how health is affected by conveyance, we turn to hospital admissions data in the next section.

V.B. Hospital Admissions

The difference in assessments and lower conveyance rates by private ambulances would be innocuous if the patients had no need for care, or if they received sufficient treatment through subsequent hospital visits. When being conveyed to the ED, a physician makes a new assessment and can decide to admit the patient to the hospital, refer the patient to another level of care, treat the patient before discharge, or discharge the patient without any treatment.[23] In all cases, the information is documented in the medical record of the patient. Thus, all conveyed patients receive some treatment by the hospital contact at the ED. In our data, we observe the hospital admission decision and the intake diagnosis. Again, we analyze these outcomes using Equation (1).

Our first outcome is whether the patient was admitted to hospital within one day of the ambulance dispatch. This short-run outcome should be less influenced by non-conveyed patients seeking supplementary care after being left at home. If private ambulance crews make correct decisions when leaving patients at home, we would expect no difference in admission rates across provider types. However, if private ambulance crews make exceptionally incorrect assessments (i.e., all non-conveyed patients are so severely ill that they would have been admitted to the hospital if conveyed), then the difference in admission rates should reflect the difference in conveyance rates of 3.2 pp.[24]

Table V, column (1), shows that if a private ambulance is dispatched, patients have a 1.2 pp lower probability of being admitted to a hospital within one day of service.[25] Under the assumption that this outcome is not related to non-conveyed patients seeking care within one day after being left at home, this means that approximately one-third of the patients left at home by private ambulance crews are so severely ill that they would have been admitted to a hospital ward if conveyed. In addition, the other two-thirds are missing out on other types of treatments and examinations that can take place even if not admitted to the hospital.

The difference in admission probability within 30 days is only somewhat lower (column (2)), indicating that only some patients who are not conveyed receive supplementary care within 30 days. Therefore, the missed opportunity of hospital admission and the health

[23]In-hospital care is important for patient health through access to advanced diagnostic tools available only when in such care. An admitted patient's diagnoses, treatments, and medications are provided by physicians who specialize in the relevant area of medicine. Moreover, once dismissed from hospital care, outpatient follow-up at a hospital-based clinic is often provided if needed. Moreover, after hospital admission, home assistance with daily tasks is organized before discharge, if necessary.

[24]Related is the prediction that if private ambulances underdiagnose, then patients conveyed to the hospital by a private ambulance should be sicker and more often admitted then patients brought by public ambulances. A regression with an admission dummy as the outcome, only for the sample of conveyed patients, yields that private ambulance-transported patients are more likely to be admitted (Coef. est. 0.0038, se 0.0017).

[25]This cannot be explained by mortality attrition, as the 1-day mortality is only 0.1 pp.

impacts thereof persist over time. In columns (3)-(6), indicators for the primary hospital intake diagnoses are used as outcomes. Column (3) shows the results for the most common cause of hospital admission, CVD. If a private ambulance is dispatched, the patients have a 0.43 pp lower probability of being admitted to hospital and diagnosed with a CVD. We also find a lower chance of admissions for diagnoses related to psychiatry, but not for respiratory or GI diseases.

Thus, the main finding is that patients with ongoing acute cardiovascular events are the ones missing out on proper treatment due to private ambulance services. CVDs comprise 36 percent of the fewer hospital admissions for private ambulance services. This result is consistent with our previous findings showing that private ambulances underdiagnose CVDs on site (see Table IV).

The missed healthcare contact, either only with an ED physician or combined with an admission, could be immensely important for the patient's health. For example, early treatment of a minor stroke or TIA can reduce the risk of reoccurring stroke by 80 percent (Rothwell et al., 2007). Moreover, not being properly examined and diagnosed can reduce access to secondary prevention treatments, such as medication, potentially explaining why we find larger effects on mortality later on (Korhonen et al., 2017; Lindahl et al., 2017; Orchard et al., 2018).

[Table 5 about here.]

V.C. Heterogeneity in the Effect of Private Ambulance Service on Mortality

A heterogeneity analysis can shed light on the patient groups most affected from having a private ambulance dispatched. In Figure III, we show the results from regression models where we interact the private ambulance dummy with a set of predetermined characteristics. We use a separate interaction model for each characteristic. The complete regression results are shown in the Online Appendix, Table B.9. Figure III shows the estimated coefficient for the interaction between the private ambulance indicator and the characteristic. An interesting pattern emerges: mortality is higher among patients with a priority 1 dispatch, for males and older people. Interestingly, patients who had *no* pretreatment hospital visits in 2007-2008 were affected more. There is no incremental effect when interacting the private indicator with different diagnoses from 2007-2008.

Thus, inferior diagnosis and treatment by the ambulance crew affect in particular historically healthier patients who do not frequently visit hospital. Since part of the diagnosis and treatment on site is a function of interviewing the patient about his or her historical health status, it is likely that historically sick people are easier to properly diagnose. A recent observational study using Swedish data corroborates this interpretation (Figtree et al., 2021). It finds that among severe AMI patients, those without risk factors had a 50 percent higher mortality within 30 days, which did not converge until after 8 years. One of the authors argues that a reason for this paradoxical finding could be that patients without risk factors are assumed by healthcare professionals to have a better prognosis and are therefore provided with less adequate treatment after the event (Hake, 2021).

[Figure 3 about here.]

V.D. Personnel Policy

An examination of newspapers, public service mass media, and information from the unions indicates differences in personnel policies between private and public ambulance providers. Here we discuss differences in collective bargaining agreements, circumvention of labor laws, on-the-job-training, and the ability to properly staff the ambulances between private and public employers.[26]

A standard working week in the public provider is 37 hours compared with 38.25 hours in private firms, a 3 percent difference. Working longer hours potentially results in lower labor costs and less well-rested personnel for the private provider. We have found no indications that there are significant differences in pension contributions for full-time employees.

One way to increase hours worked without having to pay the full wage is to schedule on-call duty time during low activity hours. According to one of the leading Swedish dailies, the independent conservative Svenska Dagbladet, ambulance staff in a private firm were normally scheduled to work 42 hours per week (including on-call duty) (Cunvik, 2011). The on-call duty could generate up to 200 additional working hours per year compared with what the collective bargaining agreement stipulated. In total, private employees could have been regularly working up to 18 percent more hours than public employees on a full-time contract.

Other differences across providers were emphasized in the renegotiation of the collective bargaining agreement with the private sector in 2017, where the new agreement stipulated adoption of the same rules as in the public sector for shift workers (almost all employees worked night shifts). This change meant that private employees would have fewer contracted hours in a full-time contract. That this change was of economic importance can be seen in how it was implemented. The union accepted that the change in shift work did not need to be implemented until the private firms had entered a new contract period with the counties.

[26] Collective bargaining agreements form the basis of "the Swedish Model", in which the conditions in each sector are determined jointly by the trade unions and the employer organizations. The government does not interfere but might set the boundaries through labor laws.

The union also accepted that the change in shift work rules would lead to lower wage increases for private firm employees in the next wage bargaining round.

Moreover, Swedish labor laws stipulate a maximum of 200 hours of overtime per year. To circumvent this law, one private firm employed its staff through a subsidiary staffing company, which essentially allowed for unrestricted overtime (Olsson, 2017; TT, 2012). In 2017, an evaluation by the county showed that private firms had on average both a higher turnover rate and a higher fraction of their staff on temporary employment contracts (SLL, 2017).

Dagens Arena, an independent left-wing newspaper, reported in 2014 that private ambulance firms were less likely to send their employees for on-the-job training, and reported that the reason was that private providers relied to a higher degree on overtime and temporary staff (Leander, 2014). Using temporary employment can save costs in many ways since it provides flexibility and fewer employer responsibilities. In general, if not negotiated otherwise, temporary staff receive approximately 5 percent lower occupational pension provision and no sick pay for the first 2 weeks of sickness if the employee was not scheduled. Temporary employees also have no general rights to preventive care subsidies. High staff turnover and strong reliance on temporary staff can make a firm vulnerable to sudden staff shortages. Public Service radio reported in 2013 that because of a staff shortage, one private provider was fined for failing to include a specialist nurse in each ambulance, as contractually obliged (SR, 2013).

Ample evidence suggests that private firms cut costs by requiring more hours and overtime, and by using fewer full-time contracts. But these measures can also lead to higher staff turnover, the recruitment of low-quality staff, and a larger share of ambulance workers that are affected by fatigue. In the following section, we address these questions by using Swedish administrative matched employer-employee data.

V.E. Staff Quality Differences

One possible explanation for the difference in outcomes between public and private ambulances comes from personnel policies affecting staff quality.[27] The literature suggests that staff quality in healthcare is important for health outcomes. For instance, Gruber and Kleiner

[27] To minimize costs, arguably, few other ways exist that could sufficiently affect quality for these firms. Firms can purchase less expensive vehicles and other supplies, although the ambulances must be equipped according to regulations and contracts. One way that better vehicles could affect health is through faster transport times. We find that private firms reach patients faster, while public firms reach hospitals faster. Jointly, total transport times between the different firms are not that different, as measured from dispatch to drop off (see the Online Appendix, Table B.4). Other equipment is also tightly regulated, and ambulance station rents are normally fixed, as ambulances often share facilities with fire brigades or occupy other fixed locations.

(2012) find that nurses' strikes in hospitals in New York in 1984-2004 increased mortality among patients admitted during the strikes by 18 percent. This effect was similar for hospitals that engaged temporary staff, stressing the importance of location-specific experience in healthcare. Bartel et al. (2014) provide evidence of the importance of nurses' job experience and education. The departure of experienced nurses, the use of temporarily contracted nurses, and the employment of new hires were all associated with longer hospital stays in the United States. Additionally, minor changes in behavior among healthcare professionals can have sizable impacts on patient health. Gruber, Hoe, and Stoye (2018) show that setting a maximum waiting time to see a physician for patients in EDs in the United Kingdom reduced mortality by 14 percent.

Ambulance services could be even more sensitive to nurses' competence relative to working in a hospital setting. In Swedish ambulances, ambulance clinicians (specialist nurses) are medically responsible for each patient and make independent decisions regarding treatments and diagnoses. Access to physician consultations and qualified second opinions are limited.[28] Patients are of all ages and suffer from many different conditions, which requires the ambulance clinician to be a generalist with a wide range of competencies.[29] Thereby, staff quality could be very important for health outcomes in our setting.

To understand whether there are quality differences between public and private employees in the ambulance sector, we link matched employer-employee data with other data sources and calculate average quality measures for the relevant years. We match all staff working for the ambulance providers and single out the ambulance clinicians (specialist nurses). Panel A of Table VI shows the differences in means between private and public employees, and Panel B shows the same mean differences restricted to specialist nurses. Starting with differences in turnover in column (1), we find that private firms have higher annual employee turnover. Approximately 12.8 percent of the employees leave the public provider every year, whereas in private firms, an additional 8.5 pp leave. Thus, the turnover rate is approximately 66 percent higher in private firms. In the private sector, staff experience is somewhat lower, and age is higher; however, neither are statistically different between providers.

We use two data sources on cognitive skills with different limitations to more directly assess staff quality differences. When using conscription data and therefore more formal cognitive test scores, the measure for cognitive skills is missing for females and for cohorts born in the mid-1980s and later. The second source is 9th grade GPA and math grades,

[28]An emergency physician is available on call but can be occupied with other calls, and the situation does not always allow lengthy phone conversations.

[29]Furthermore, compared with other nurses who can follow-up on patients as they are thoroughly diagnosed by a physician, the ambulance staff in Stockholm does not have structured access to feedback on their medical decisions. Thus, ambulance staff can rarely evaluate whether their decisions or diagnoses were correct.

both normalized to a mean of zero and a standard deviation of one by each cohort. For these outcomes, we can observe only those who graduated after 1987, i.e., cohorts born after 1972. Although somewhat imprecisely measured, the overall picture is that employees in private firms score lower on these cognitive skills measures as shown in columns (4)-(6). For example, private specialist nurses have 23 percent of a standard deviation lower GPA in 9th grade than public nurses.

Finally, there is a striking difference in annual wage income, as shown in column (7). For all employees, the annual gross wage is approximately 9 percent higher in the private sector. As the average threshold for state taxes, 20 percent on the margin, was approximately 42,000 EUR during the study period, the difference in net wage is also 9 percent. For specialist nurses, the gross wages are 11 percent higher in the private sector but somewhat less in net wages—approximately 10 percent—due to the extra marginal tax. In our discussions with the unions and representatives of the public provider, there were no indications of significant differences with respect to additional job benefits, such as pension schemes, parental leave compensation or vacation benefits for regular employees.

Since we argue that our results are consistent with private firms cutting costs with an adverse effect on quality, it may seem counter-intuitive that annual wages are about 10 percent higher in private firms. Although some job factors (less on-the-job-training and more scheduled on-call duty time) seem inferior in the private sector, a 10 percent difference in wages is quite high. Moreover, considering the excessive turnover at private firms, a compensating wage differential explanation also seems implausible.

Hence a more likely explanation is that the annual wage difference comes from longer working hours. Section V.D. shows that private firm regular full-time contracts stipulate 3 percent more hours and that the use of overtime at these firms is extensive. A crucial piece of information is found in the evaluation of the firms' output in 2017 (SLL, 2017), according to which private firms produced 713 ambulance hours per regular employee in 2017, whereas the public provider produced 582 hours—a 23 percent difference (SLL, 2017). If ambulance firms used no temporary staff, this would be enough evidence to show that private firms have lower labor costs per hour since their employees work 23 percent more but only have 10 percent higher incomes. However, Section V.D. also indicated that temporary employees were used more in the private sector. Adjusting for the number of temporary staff, also reported in the evaluation, the difference in ambulance hours per all employees indeed decreases to 17 percent.

That private firms produce more ambulance hours per staff can mean either that their temporary staff work more hours or their regular employees work more hours. Fortunately, we can identify temporary workers in the matched employer-employee data. Importantly, we have no indications that hourly wages would be different for temporary staff across provider type. Thus, if the average income is higher for private temporary employees, then they work more hours, and our estimate of a 17 percent difference in working hours for regular employees in the private sector is an overestimate.

Online Appendix Table B.10 shows the annual wages in 2017 for regular and temporary workers, both for all employees and for specialist nurses. Again, there is a difference in income both for all employees and for specialist nurses for regular employees in favor of private firms (about 7 percent). For all temporary employees, there is no difference across provider types. For the subgroup of temporary employed specialist nurses in the private sector, wage income is somewhat lower, indicating that a private temporary nurse works *fewer* hours on average.

Thus we conclude that private employees work at least 17 percent more hours and are paid 10 percent more, and that the hourly wage is at least 7 percent lower in the private sector. This figure is supported by Statistics Sweden, which estimates the equivalent full-time monthly salary (i.e., adjusting for overtime) for ambulance nurses across sectors in Sweden. For 2017, they reported that the monthly salary was 3.770 EUR for the public sector and 3.580 EUR for the private sector, a 5 percent wage advantage for public sector nurses (SCB, 2018).

[Table 6 about here.]

V.F. Effect Size Magnitude

In this section, we discuss the plausibility of the estimated effect size given our suggested mechanism: non-conveyance. If non-conveyance is the sole cause of the mortality difference between public and private ambulances, we can estimate the effect of non-conveyance on mortality for "compliers". That is, we can estimate the effect of non-conveyance on mortality for the patients who are conveyed to hospital if a public ambulance is dispatched but who are left at home if a private ambulance is dispatched. For this exercise to be valid we need to assume that an exclusion restriction holds, i.e., the only channel by which private ambulances can affect mortality is through the conveyance decision. Thus, we must assume there is no effect of misdiagnosis and that the correct guidelines are being followed, which includes sending the correct information to the hospital as discussed in section V.A. In addition, we must also assume that there are no differences in the care provided on site or in the ambulance, i.e., levels of skill or fatigue across providers are not important.

Under the exclusion restriction, we find that the local average treatment effect (LATE) of non-conveyance is 8 pp for 1-year mortality, where we have scaled our reduced form effect of 0.0026 with the first-stage effect, i.e., the difference in conveyance rate of 0.0032 (see Table IV) between private and public ambulances. In other words, this estimate implies that the mortality rate is 44 percent higher for patients conveyed by private ambulance than by public, i.e., 0.08/0.18 where 0.18 is the 1-year mortality rate among patients transported by public ambulance. Reassuringly, we also find that the LATE effect on 3-year mortality is almost the same, i.e., 43 percent.

To assess the plausibility of the magnitude of this LATE effect, we argue that it possible to compare it with estimates in the medical literature on related treatments. One such related intervention is for patients with a CVD, because this population suffers from a similar type of acute medical condition to those patients requiring ambulance transport. Indeed, medical problems related to CVDs are often acute in nature, such as a stroke or an AMI, which makes these diseases more comparable to our setting than papers evaluating treatments for psychiatric or respiratory diseases, which are more often chronic. Moreover, CVD patients are also a relevant population for our study since they contribute significantly to the effect of the private ambulance service that we are measuring. Indeed, we find that private ambulance staff underdiagnose CVDs, and CVD patients make up around 20 percent of all the patients transported to hospital via public ambulance service. Moreover, 25 percent of the patients admitted to hospital via public ambulance have a CVD as their main complaint.

The medical literature shows that correct, timely medical treatment by specialists can reduce mortality among CVD patients by 26 to 65 percent.[30] Our estimated effect on mortality of not being transported to hospital when experiencing an acute medical condition was 44 percent for one-year mortality and 43 percent for three-year mortality. Thus, our effect sizes line up well with the estimates from the medical literature on CVD treatment and strengthen the case that the most important mechanism affecting mortality differences across provider type is the conveyance rate.

[30] Several studies have documented that proper medical treatment, timely treatment, and treatment by specialists can have considerable effects on morbidity and mortality for patients with CVDs (Hart, Pearce, and Aguilar, 2007; Kapral et al., 2016; Rothwell et al., 2007). Early treatment of a minor stroke or TIA can reduce the risk of reoccurring stroke by 80 percent (Rothwell et al., 2007). Additionally, being referred to a stroke prevention clinic from the ED can lead to 26-50 percent lower 1-year mortality than that of patients who are not referred (Kapral et al., 2016; Webster et al., 2011). Moreover, patients who fail to seek care at an ED are also at risk of missing out on important secondary prevention treatments. Non-adherence to medications after an AMI can increase the mortality risk by up to 65 percent three years after the event (Korhonen et al., 2017). Moreover, providing anticoagulant agents to arterial fibrillation patients can reduce the risk of stroke by 60 percent and all-cause mortality by 26 percent (Hart, Pearce, and Aguilar, 2007). The effect size magnitudes for the treatments analyzed in these papers give us a plausible range against which to compare our effect sizes.

V.G. Competing Mechanisms

In this section, we discuss competing mechanisms and provide some indirect tests. We acknowledge that it is difficult to quantify or rule out competing mechanisms, and that the tests provided are only suggestive.

One could consider other sorting mechanisms not related to the private firms' production choices, as in Hart, Shleifer, and Vishny (1997). It may be a disadvantage to have the ambulance station located far from the central part of Stockholm (e.g., access to public transport and places to eat). Better nurses may therefore prefer to work for public ambulances, as public stations are often located centrally. In Table B.3 in the Online Appendix, we restrict the sample to include only stations in the inner city and other proximate parts of Stockholm. In the restricted sample, the amenities are similar and the commuting time with public transport to the city center of Stockholm is about 30 minutes, at most. However, our results are robust when using this subsample.

A related sorting theory could be that highly skilled personnel want to work for public ambulances and that the skill distribution of ambulance nurses is fixed. Then, average performance is not affected by changes in institutional arrangements. Figure A.4 in the Online Appendix plots the number of specialist nurses residing in Stockholm and relates that to the number of specialist nurses in the ambulance sector. After standard in-house training for 10 weeks, any specialist nurse is eligible to work in an ambulance. Figure A.4 indicates that a large number of specialist nurses live in Stockholm County (a factor of 10 larger than the pool of ambulance nurses). However, this may not be a potential pool to recruit from if the highly skilled nurses' preferences are skewed in favor of a public sector job. In Table B.6 in the Online Appendix, we test for this by studying transfers of nurses between providers. We find that there is substantial movement between sectors. For example, in relation to average annual turnover in the public provider, 23 percent (0.0289/0.1277) of the nurses move to a private ambulance firm on average each year. Moreover, we find no statistical difference between the relative flow of nurses from private to public ambulance firms and from public to private (Table B.6, column (4)). We believe this speaks against strong preferences in favor of working for a public ambulance provider.[31] Moreover, as shown in column (3) of Table B.6 in the Online Appendix, exits from the ambulance sector are more common for employees in private firms. Although this result could be generated by the selection of workers, it indicates that the market is not fixed and that poor working conditions in private

[31] A related theory is that if working in a public ambulance provides better opportunities for moving to a career in public hospitals, working for the public firm should attract the best nurses. Evidence against this type of sorting is provided in the Online Appendix, Table B.6, column (5), where we find no predictive power of the ambulance nurse provider type on the probability of changing jobs to work in a public hospital.

firms could reduce the supply of ambulance staff.

V.H. Threats to Identification: Robustness

Many factors could threaten the internal validity of our design. In Figure IV, we address several issues related to ambulance services and market structure by displaying the point estimates with corresponding 95 percent confidence intervals for a range of specifications. Using three-year mortality as the outcome, the first row displays the bivariate, noncausal correlation. This correlation is negative and substantial in size, reflecting the fact that patients serviced by private firms are healthier. This finding is expected, as private firms service a younger population on average, as shown in the left Panel of Figure I.

The second row shows that when adding the grid, year, and month fixed effects, the estimated effect switches sign and becomes positive and of a similar magnitude as in our preferred model. However, this specification may be problematic, as priority is part of the treatment allocation mechanism. For ambulance dispatchers, in addition to the locations of the patients and ambulances, this is the most vital piece of information they have. Nevertheless, flexibly controlling for patient priority has no effect on the point estimates (third row). This model is also the preferred model that we utilize more broadly in the paper.

We have shown how mortality responds to private providers as we implement our preferred model. We continue presenting reasonable deviations from this model to demonstrate the robustness of our results. Each row in Figure IV refers to a new robustness check. For brevity, we describe and explain all specifications in the Online Appendix Section D, and here highlight only the 4 final specifications, rows (15)-(18). We consider time as a possible confounder for our results. If patients' health conditions are correlated with the treatment assignment through the time of day (or day of the week), we could be estimating a spurious relationship. Private ambulances could work more often in certain districts at certain times during the day or on certain dates when patient characteristics are different or the health environment is altered (e.g., during nights). If this is the case, our estimates should be sensitive to more flexible time controls. However, the results do not change if we include unique month fixed effects, unique week fixed effects, unique day fixed effects, or even fixed effects by each unique hour (rows (15)-(18)).[32]

[Figure 4 about here.]

Although we have considered several potential differences between the private and public ambulance districts, there can still be more subtle differences that we do not capture. The

[32] In the Online Appendix, Section D, we replicate the same results in Figure D.4 for 2-year mortality.

composition of patients in areas served by public ambulances might differ in a way that makes patient knowledge very important and hence grants ambulances a quality advantage in their "own" districts. Private ambulances would then perform poorly in "public" districts but well in their own districts. To test this hypothesis, we divided Stockholm into private and public districts based on the geographical area that surrounds each ambulance station. These districts are well defined by the dispatch services but not binding for their ambulance allocation decisions. We separately estimate Equation (1) for private and public districts using 3-year mortality as the outcome and report the results in the Online Appendix, Table D.1. We find that the effect of private service on mortality is similar in both samples and that the estimates are statistically indistinguishable from one another.

Another way to make our identification strategy more credible is to focus on grid cells where the probability of being serviced by a private ambulance is close to the probability of being serviced by a public ambulance. If much of our identifying variation comes from grid cells with poor overlap between private and public ambulances, our approach would be problematic. In grid cells with poor overlap, the risk of nonrandom assignment of ambulances to patients is higher. Grid cells with an even distribution of private and public ambulances are neighborhoods with a similar distance to a public and a private ambulance station or around the borders of their respective districts. In these grid cells, the probability of being serviced by a private ambulance is close to 50 percent. To approach this problem, we take the average of the dummy variable *Private* within each grid cell and year and condition our regression models on there being a certain fraction of private ambulance dispatches in each cell. In the Online Appendix, Figure D.1, these results are shown for the fractions 0.1-0.9, 0.2-0.8, 0.3-0.7, and 0.4-0.6. We find that the results line up well across these different samples, even though in our most restricted sample, we utilize only 10 percent of the full sample. These findings suggest that border regions between private and public ambulance stations provide much of the identifying variation that we use for the estimation.

VI. Conclusions

The provision of public services is often outsourced to private firms to help the public sector contain costs. Private firms have incentives to reduce costs but can have weak incentives to uphold quality if it is not explicitly contracted for. When quality can be contracted for, private firms can theoretically produce adequate quality at a lower cost.

We test these predictions in healthcare, a sector that has received little attention in the economics literature on outsourcing. Health outcomes are often difficult to contract for, as they may reflect the characteristics of patients rather than the quality of the provided health service. For the same reason it is often difficult to evaluate different providers' impact on quality

We solve the empirical challenge in an ambulance services environment where both private and public providers operate side-by-side and where ambulance assignment is as good as random. We confirm that private firms reduce costs and are more efficient with respect to contracted outcomes, but have inferior performance on noncontracted health outcomes. Patients serviced by private ambulances have higher mortality within one day and up to three years after being serviced. For any given year of the contract period, approximately 420 additional patients died within 3 years because a private ambulance was dispatched. Our calculations suggest that the loss in terms of the value of quality adjusted life years could be substantial. Even conservative estimates indicate that the cost could be approximately one-quarter of the total cost of ambulance services and almost twice as high as the maximum cost savings generated by outsourcing.

We provide evidence of the mechanism underlying the results, showing behavioral differences between ambulance providers during assignments. In particular, we find that private ambulances underdiagnose patients and leave a substantially higher number of patients at home. Causal estimates are complemented by descriptive evidence suggesting that private firms have higher turnover, require more hours from their staff, rely more on overtime, and provide less on-the-job training. We also find indications of lower cognitive skills among private staff.

When quality is difficult to contract for, policy makers inclined to outsource public services attempt to solve this dilemma by contracting for proxies or for inputs that are assumed to be related to quality. However, this procedure is subject to moral hazard and provides strong incentives for firms to comply with contracted measures while neglecting unmeasured aspects of quality. Our empirical evidence confirms this theoretical prediction in the ambulance services sector. One solution for the client could be to write more detailed contracts with the private ambulance provider; however, this severely limits private firms' ability to lower costs. Instead, the literature has described an intermediary solution to this problem, namely, engaging not-for-profit private firms (Glaeser and Shleifer, 2001). These not-for-profit firms can potentially leverage innovative pressure while committing to softer incentives and may be a suitable choice in the ambulance sector if in-house production is inefficient.

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Supplementary Material

An Online Appendix for this article can be found at The Quarterly Journal of Economics online.

Data Availability

Code replicating the tables and figures in this article can be found in Knutsson and Tyrefors (2022) in the Harvard Dataverse, https://dataverse.harvard.edu/dataverse/knudan/

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TABLE I

CONTRACTED PROVISIONS AND COSTS OF PUBLIC AND PRIVATE AMBULANCES FOR AUCTIONS IN 2011

Provider	Hours per year	Market share	Annual compensation (€)	Cost per ambulance hour (€)
Public	136,929	33 percent	15,900,000	116.7
Private	274,248	67 percent	25,741,026	93.9

Notes. The authors' calculations from the contracts and corresponding documents describing the auction in 2011. We convert exchange rates by 1 EUR=10 SEK.

TABLE II

CONTRACTED OUTCOMES

	Response time to dispatch	Travel time to patient
	(1)	(2)
Private ambulance	-8.31	-61.14
	(0.88)	(5.29)
Public outcome mean	108	717
Observations	1000902	1017910

Notes. Each column display results from a separate regression following Equation (1). The two outcomes are measured in seconds between two time stamps. Each model includes 850x850 grid fixed effects covering the entire county of Stockholm, where each grid is approximately 190x130 square meters in size, as well as year and month dummies and priority of patient dummies. Standard errors are clustered at each grid cell.

TABLE III

NONCONTRACTED OUTCOMES: MORTALITY

	Mortality after ambulance transport occurred within:							
	1 day	1 week	1 month	3 months	6 months	1 year	2 years	3 years
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Private ambulance	0.0010	0.0009	0.0014	0.0023	0.0011	0.0026	0.0041	0.0042
	(0.0003)	(0.0005)	(0.0008)	(0.0010)	(0.0011)	(0.0013)	(0.0014)	(0.0015)
Public outcome mean	0.0148	0.0294	0.0580	0.0954	0.1290	0.1758	0.2477	0.3066
Observations	1075958	1075958	1075958	1075958	1075958	1075958	1075958	1075958

Notes. Each column display results from a separate regression. The outcomes are dummy variables indicating whether the patient died within each time window. Each model includes 850x850 grid fixed effects covering the entire county of Stockholm, where each grid is approximately 190x130 square meters in size, as well as year and month dummies and priority to patient dummies. Standard errors are clustered at each grid cell.

TABLE IV

DOES FIRM AFFILIATION AFFECT AMBULANCE CREW BEHAVIOR?

	Diagnoses set by ambulance crew							
	Unspecified/ General	CVD	Psychiatric/ drugs	Respiratory diseases	GI diseases	Cardiac arrest	Severity (more severe)	Patient stays home
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Private ambulance	0.0139	-0.0059	-0.0006	-0.0015	-0.0011	0.0003	-0.0523	0.0322
	(0.0010)	(0.0010)	(0.0007)	(0.0009)	(0.0007)	(0.0002)	(0.0029)	(0.0011)
Public outcome mean	0.0399	0.1364	0.0594	0.0910	0.0545	0.0046	2.8507	0.1010
Observations	1075984	1075984	1075984	1075984	1075984	1075984	1061675	1075984

Notes. Each column reports results from a different regression, where each model includes 850x850 grid fixed effects covering the entire county of Stockholm, for which each grid is approximately 190x130 square meters in size, as well as year, month, and priority to patient indicator variables. The diagnoses set by the ambulance crew are obtained from the ambulance data. The ambulance report requires a listing of the diagnosis, which is chosen from approximately 160 common conditions. In column (1), the outcome is an indicator variable denoting whether the ambulance crew chose an unspecific category, e.g., "General, unspecific." In column (2), the outcome variable indicates whether the ambulance crew chose a category consistent with a CVD disease, e.g., cardiac arrest, chest pain, AMI, or stroke. In column (3), we use an indicator variable for psychiatric diagnoses as the outcome, including all intoxications by drugs, medicines, alcohol, and toxic chemicals. The outcome in column (4) indicates whether a respiratory disease, such as COPD, the common flu, and respiratory distress, was listed as the main diagnosis. The outcome in column (5) indicates whether gastrointestinal diseases were the diagnosed complaints, such as abdominal pain or ulcer. In column (6), we single out cardiac arrest from the CVD category as a standalone outcome using three listed conditions, including the term "cardiac arrest." Further information on the ambulance crew diagnoses can be found in Section F in the Online Appendix. The outcome in column (7) is a severity measure reported by the ambulance crew that ranges from 0 to 7. The outcome in column (8) is a variable recorded by the crew that indicates whether the patient was transported by the ambulance or left at home. Standard errors are clustered at the grid cell level.

TABLE V

Does Ambulance Firm Affiliation Affect Hospital Admissions?

			Primary intake diagnosis			
	Patient admitted $\leq$ 1 day	Patient admitted $\leq$ 30 days	CVD	Psychiatry/ drugs	Respiratory diseases	GI diseases
	(1)	(2)	(3)	(4)	(5)	(6)
Private ambulance	-0.0123	-0.0086	-0.0043	-0.0017	-0.0008	0.0007
	(0.0015)	(0.0014)	(0.0012)	(0.0006)	(0.0007)	(0.0006)
Public outcome mean	0.5581	0.6232	0.1065	0.0384	0.0615	0.0392
Observations	1075984	1075984	1075984	1075984	1075984	1075984

Notes. Each model includes 850x850 grid fixed effects covering the entire county of Stockholm, where each grid is approximately 190x130 square meters in size, as well as year, month, and priority to patient indicator variables. Each column describes a different regression. In column (1), the outcome is an indicator variable denoting whether the patient was admitted to a hospital the same day or the day after the ambulance dispatch. We use both these days because waiting times at the ER can result in admissions taking place the following day, and we cannot determine whether a conveyance resulted directly in an admission. In column (2), the outcome variable indicates whether the patient was admitted at any time within 30 days of the ambulance dispatch. In columns (3)-(6), the outcomes represent the main intake diagnoses for patients admitted to a hospital within 1 day of ambulance dispatch (as in column (1)). Intake diagnoses have been coded based on the first letter in the ICD10 coding system for the primary diagnosis in the data. See the Online Appendix, Figure F.1, for the results of all available categories. Standard errors are clustered at the grid cell level.

TABLE VI

FIRMS AND EMPLOYEES

	Turnover	Experience (Ambulance firm years)	Age	Cognitive skills (conscription)	9th grade GPA	9th grade math grade	Annual Wage income (EUR)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: All employees							
Private ambulance	0.085	-0.197	1.035	-0.245	-0.137	-0.098	3307.519
	(0.011)	(0.417)	(0.622)	(0.139)	(0.075)	(0.077)	(669.727)
Public outcome mean	0.1277	8.4445	41.2344	5.0774	-0.061	-0.044	36271.5797
Observations	5436	5436	5436	1776	2321	2321	5436
Panel B: Specialist nurses							
Private ambulance	0.069	-0.558	0.678	-0.227	-0.228	-0.163	4429.354
	(0.019)	(0.654)	(0.966)	(0.232)	(0.096)	(0.111)	(1186.151)
Public outcome mean	0.1625	7.6989	39.9034	5.4283	0.248	0.183	39477.7871
Observations	1869	1869	1869	560	1046	1046	1869

Notes. Each model includes year dummies and the years 2009-2016, unless otherwise noted. In column (1), the outcome variable *Turnover* is an indicator variable that takes a value of 1 if an employee is observed in a specific ambulance firm in year t but not in $t+1$. This variable is a combination of employees exiting the sector and employees changing employer (if we use only the new contract period, 2012-2016, we find a smaller but significant estimate of 0.04 for all employees). In column (2), the outcome *Experience* is a variable that describes how many years an employee has potentially been working in the ambulance sector in Stockholm (in one of the firms operating in 2009-2016), with 1990 as the earliest year of observation. In column (3), age in years is the outcome. In column (4), the outcome is cognitive skills measured in Swedish conscript data and the cognitive tests available therein. We use the average score on 4 tests measuring logical, verbal, technical, and spatial skills that are standardized to a standard nine scale (1-9) as the outcome. For men, these data are available with full coverage only before the early 1980s; the data provide poorer coverage of younger men born in the mid-1980s, when mandatory conscription was phased out, or later. Columns (5) and (6) use register data on grades (from the 9th grade) available from 1988 until today. We use the GPA in column (5) and the math grade in column (6) as the outcomes; both variables are normalized to a mean of zero and a standard deviation of one by each cohort. These data are available for both men and women but only for individuals born after 1971. In column (7) we use the yearly wage income as the outcome (using the exchange rate 1 EUR=10 SEK) according to each individual's filed tax report. Panel A shows the results for all employees, and Panel B shows the results only for nurses with a specialist degree. For further details, see the Online Appendix, Section F, which describes the firm data. All data on firms and employees come from the FAME database. Standard errors are clustered at each individual employee in the data.

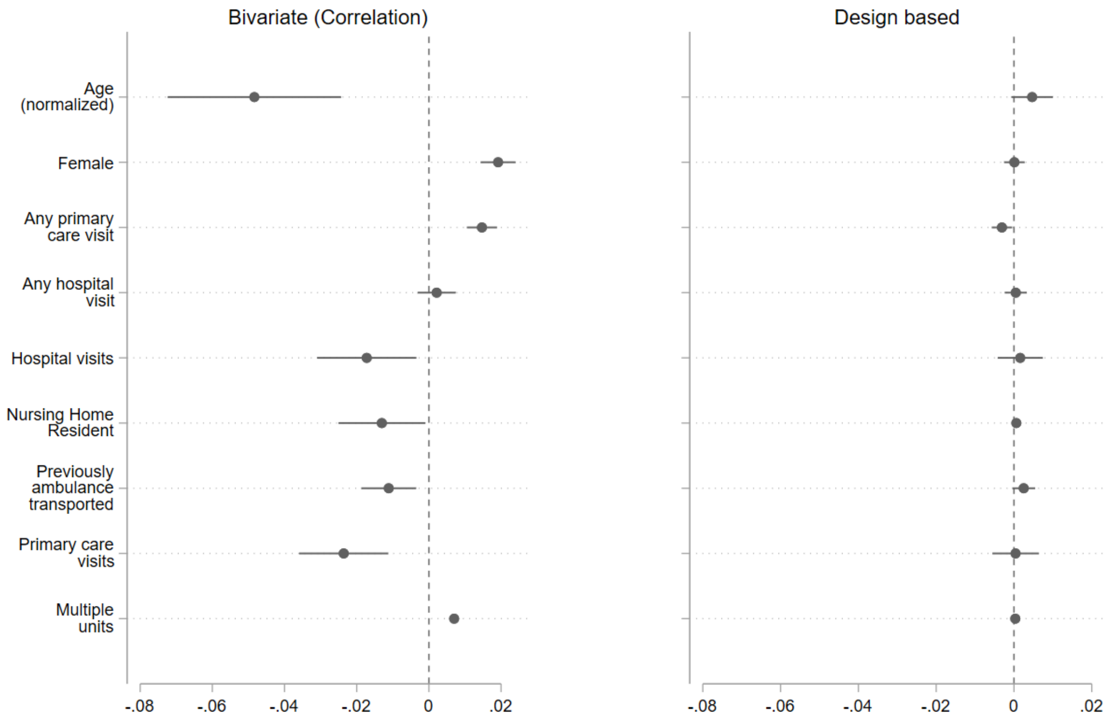

FIGURE I

Balance of Predetermined Variables: Bivariate and Design Based

Both panels show estimates of *Private*, with the predetermined variable indicated to the left of the figures as the outcome. The left Panel shows the bivariate linear regression estimate using OLS (only the outcome and private ambulance indicator), whereas the right Panel displays the same results using our preferred model. Several variables here are measured at the time of each ambulance transport. Age in years (normalized by demeaning and dividing by the standard deviation), sex, residing in a nursing home, dead on arrival, multiple units dispatched (to the same patient), and previously transported by an ambulance (after 2009) have this property. Primary care and hospital care visits are based on data from 2007-2008. All regression models include year, month, and dispatch priority dummies. We include 850x850 grid fixed effects and cluster the standard errors at the grid cell level.

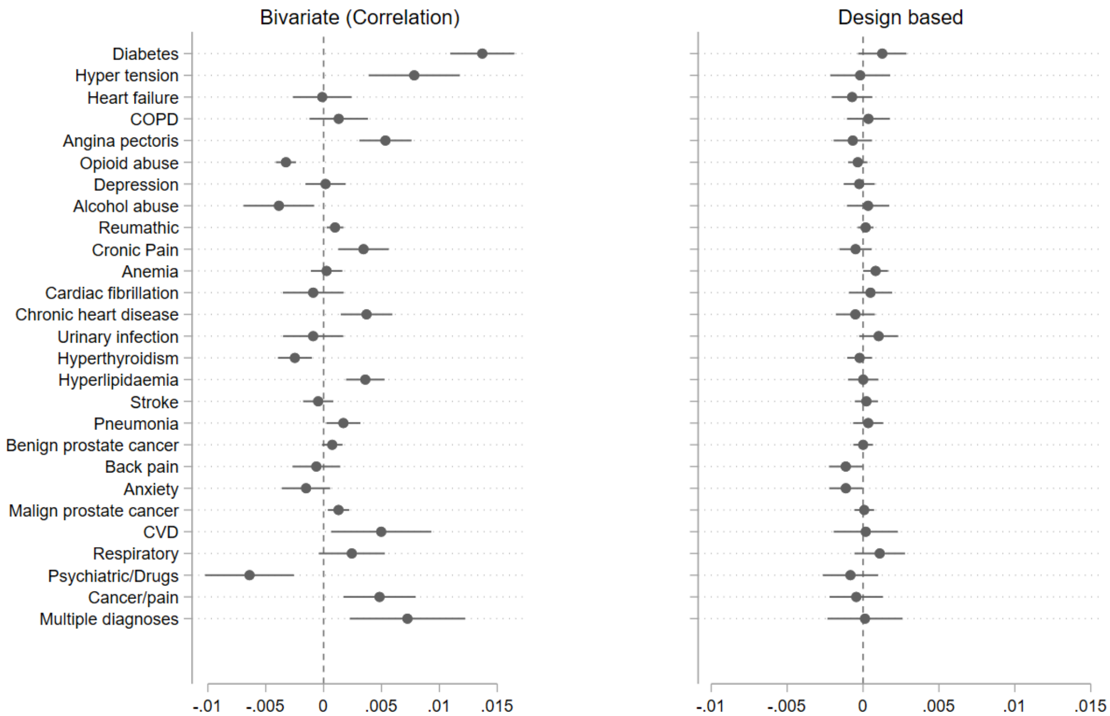

FIGURE II

Balance of Diagnoses in 2007-2008: Bivariate and Design Based

Both panels show estimates of *Private*, with the predetermined variable indicated to the left of the figures as the outcome. The left Panel shows the bivariate linear regression estimate using OLS (only the outcome and the private ambulance indicator), whereas the right Panel displays the same results using our preferred model. Diseases are based on ICD-10 codes registered at the hospital and primary-care visits between 2007 and 2008. The diagnoses that we choose to include are the most frequent that we could find in the data. If a diagnosis is documented, the patient indicator variable for that disease is 1. If no indication exists, it is 0. All regression models include year, month, and dispatch priority dummies. We include 850x850 grid fixed effects and cluster the standard errors at the grid cell level (also in the bivariate regressions).

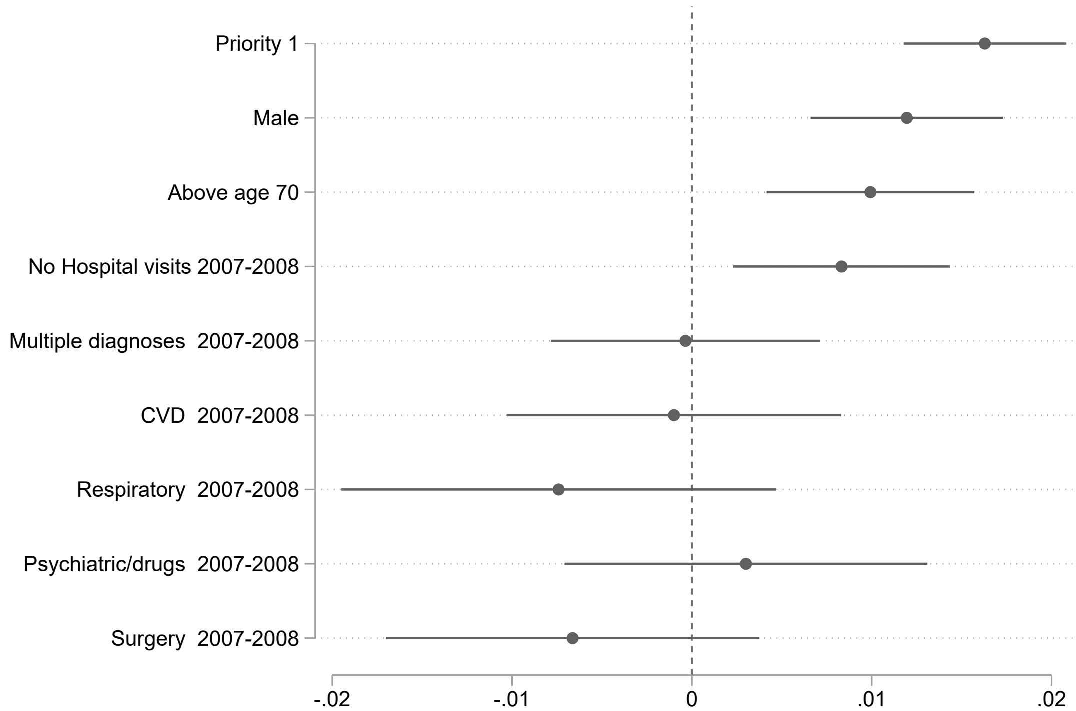

Figure III

Heterogeneity in the Treatment Effect: 3-Year Mortality

Each model includes 850x850 grid fixed effects covering the entire county of Stockholm, where each grid is approximately 190x130 square meters in size, as well as year, month, and priority to patient indicator variables. Each row represents a separate regression where the dummy variable for private ambulance is interacted with a predetermined characteristic. The main effects are included, but only the interaction term is presented in the figure. See the Online Appendix, Table B.9, for a more thorough description of the models. In row (1), the interaction variable is created by interacting the private dummy with a binary variable indicating whether the priority to the patient was a priority 1 dispatch. In row (2), the interaction variable is created by using a "male" dummy. The interaction variable in row (3) is created by using a binary variable to denote whether the patient is older than 70 years of age. In rows (4)-(9), we use the predetermined health variables measured in 2007-2008 and add them together into 6 distinct categories: any hospitalization, more than 1 diagnosis, any CVDs, any respiratory diseases, any psychiatric conditions and drug abuse, and any surgical diseases, including cancer and pain conditions. Standard errors are clustered at the grid cell level.

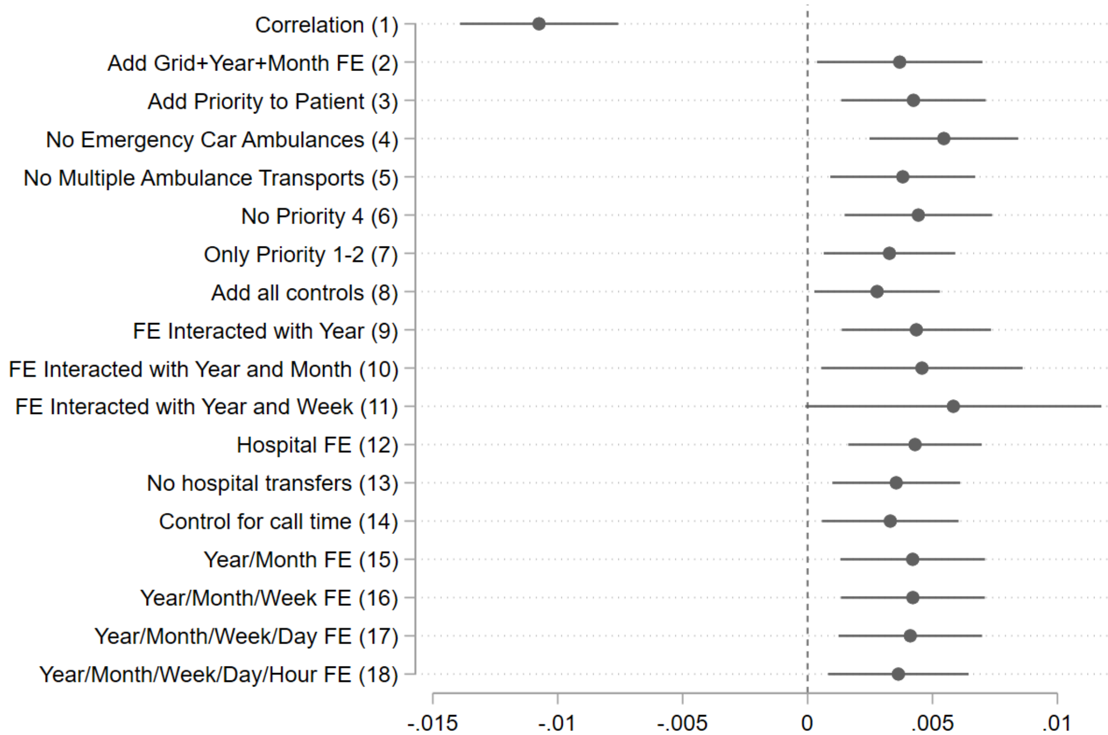

Figure IV

Robustness: Deviations from the Basic Model (3-Year Mortality)

This figure presents point estimates and 95 percent confidence intervals for different specifications of Equation (1). The first two rows impose fewer restrictions than Equation (1). The first row is the raw correlation between 3-year mortality and private ambulance providers. Row (2) adds fixed effects, leading up to our preferred specification in row (3), which also includes priority to patient indicators. Row (4) and below challenge this specification by adding structure or restricting the sample in different ways, as described in the table and the text. Standard errors are clustered at the grid cell level.