Workhour Normality and Gender Gaps: Evidence from Brazilian Exporters

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Abstract

Workhours are 'normal' when they match the rest of the economy and are regular. Exporting firms' foreign trading partners often operate in different time zones and can induce abnormal working hours. Using a comprehensive employer-employee matched dataset from Brazil, I show that the further away an exporting firm's trading partner is temporally, the wider are the gender gaps in employment and earnings in exporting firms. Two extra hours of difference of an exporter from their trading partners lead to a decrease in the proportion of female employees by 1.2 percentage points, and a rise in the earnings gender gap by 0.84 percentage points. This accounts for more than 40% of the extra gender earnings gap seen between exporting firms and domestic firms. Exporters pay a premium to all their employees but this "exporter wage premium" is 2 percentage points smaller for women workers. Temporal distance explains 42% of this difference. Exporters' temporal distance leads to a 0.15 percentage point widening of the gender earnings gap in the whole Brazilian formal economy, which is an increase of 1.2%. Men's earnings are unaffected by the temporal distance to their trading partners. The contractual basic salary and hourly wage rate are unaffected by temporal distance, and contractual hours are only marginally affected. Rather, the difference in earnings arises due to overtime pay, commissions, and bonuses. Using a panel event study design, I also find that new mothers are 2.6 percentage points more likely to leave exporting firms with far away trading partners than they are to leave exporting firms with closer partners within a year of giving birth. This difference becomes stark again as their children reach school-going age. Schoolhours overlap, the overlap between Brazilian schoolhours and trading partners' workhours, is also the most potent temporal measure, suggesting that childcare is an important driver of these effects. The earnings gap is worsened amongst white collar workers and managers, but not amongst blue collar workers, emphasizing that temporal distance matters because it creates frictions in synchronous communication and management.

1 Introduction

Many gaps remain between men and women's socio-economic outcomes, from labor force participation rates and wages to the number of Fortune 500 CEOs. A number of possible explanations for these gaps have been considered and evaluated in the social science literatures. There is substantial evidence of women paying marriage penalties and motherhood penalties.[1] More recent work has shown that non-cognitive skills (like negotiation)[2] and psychological attributes (like risk aversion and preference for competition)[3] contribute to gendered occupational sorting and contract selections. Social norms can limit women's labor force participation and earnings.[4] There is also evidence of prejudicial discrimination against women in the labor market.[5] Some of these factors hold more sway than others, but none explain all of the gap.

In this paper, I examine the role of a relatively less studied reason related to personnel economics – workhour normality. Workhours are 'normal' when they match the rest of the economy and are regular. I exploit the abnormal workhours induced by exporting firms' foreign partners and clients to measure the importance of workhour normality in determining the gender gaps in employment and earnings. The further away a trading partner is temporally, the worse hours might be demanded from the employees. Are gender gaps worse within firms with further away clients? Exporting firms pay an "exporter wage premium", but this premium is smaller for women. Can abnormal workhours explain the smaller "exporter wage premium" that firms pay women? Are these effects worse for mothers? I use employee-employer matched data from Brazil (which contains the universe of all formal sector firms and employees) to explore these questions. Municipality-commodity level export data allow me to determine the location of exporting firms' trading partners, and the severity of the workhour abnormality induced.

Workhour normality is the amenity of working regular hours (say, 9 to 5) that different firms and roles provide to differing degrees. This can be contrasted with being "on call" and providing "face time" whenever required. Some jobs require more temporal flexibility: employees are expected to be around to service clients and attend meetings at odd hours. Wages can be tied to the ability of employees to be available at abnormal hours, or conversely, penalties might be imposed if employees are unable to do so. Note that abnormal workhours do not necessarily mean longer hours, though the two could be correlated. This demand for working abnormal hours can lead to firms offering differing wage-contracts based on whether or not an employee is able to meet these requirements. If employees are able to surpass some minimum number of abnormal hours, they might be paid at a higher *rate* than their counterparts who are unable to.[6] Then, if there are systematic differences in the ability of one group of potential employees to provide their labor at odd hours, they would end up accepting the contract (perhaps implicit) that pays less, and a gap in earnings might emerge. Alternatively, they might not choose to work at these firms at all, and a gap in employment might arise.

Women in general, and in Brazil in particular, have a lower ability than men to be flexible with their work schedules and work abnormal hours. The gendered division of household labor often means that a heavier burden of housework falls on women, whether they are also employed outside the household or not.[7] Mothers are still seen to be more responsible for

[1] See Anderson, Binder, and Krause (2002), Pertold-Gebicka, Pertold, and Datta Gupta (2016), Adda, Dustmann, and K. Stevens (2017), Bursztyn, Fujiwara, and Pallais (2017), and Kleven, Landais, and Søgaard (2019).

[2] See Tognatta, Valerio, and Sanchez Puerta (2016) and Ashraf et al. (2018).

[3] See Croson and Gneezy (2009) and Bertrand (2011) for reviews of this literature.

[4] See Jayachandran (2020) for a review in developing country contexts. See also Liu and Vikat (2004), Bertrand, Kamenica, and Pan (2015), and Codazzi, Pero, and Albuquerque Sant'Anna (2018) for how a norm dictating that wives should earn less than their husbands limits women's earning potential.

[5] See Charles, Guryan, and Pan (2022).

[6] Goldin (2014a) discusses a model (based on Rosen (1986)) that shows how these requirements can lead to a convex relationship between hours worked and earnings.

[7] See IBGE (2018) and Charmes (2019).

childcare than fathers.[8] This becomes very relevant in this setting as less than a third of Brazilian children under three have access to a creche or day care services.[9] Brazilian law also mandates compulsory schooling for all children above 4, and it sometimes becomes incumbent on the mother to ensure attendance. Furthermore, safety is a serious concern in many Brazilian locales, and the rates of gender-based violence (both at home and outside) are amongst the highest in the world.[10] This adds another pressure against working at odd hours and after dark, or changing one's schedule at a short notice.

At the same time, certain kinds of firms demand that their employees work unusual hours and have a stronger requirement of flexibility from their employees. For example, call centers servicing foreign clients have to shape their work schedule according to the time at their clients' location. Multi-national firms with personnel spread across the world have to schedule meetings at times that accommodate all participants, and this may result in calls outside normal workhours. Chauvin, Choudhury, and Fang (2020) show that an increase in temporal distance reduces intra-firm communication for routine tasks and forces non-routine tasks requiring synchronous communication to be shifted into leisure time. This leads to the main hypothesis of this paper: given that female employees tend to have a higher preference for workhour normality, are the gaps in participation and earnings higher in such firms?

There are many ways in which these gaps could be manifest themselves in practice. Women might self-select out of working at these firms either by not applying for such positions at all, or by leaving when the requirements become too stringent. Anticipating this, firms might also screen out women. Even conditional on employment at such firms, women may pay a workhour normality penalty. They might be choosing the roles or contracts that have laxer temporal requirements with lower pay. They could be placed in lower-paying domestic divisions within the firm, or they might not be promoted to client-facing or leadership roles that require regular interactions with clients.

Before implementing my main strategy, I document certain stylized facts about exporting firms and the gender gaps which motivate further analysis: exporting firms employ a lower proportion of women, pay an "exporter premium" (which is smaller for women), and also exhibit a higher earnings gap. However, since exporting firms are likely to be systematically different from domestic firms in terms of size[11] and productivity[12], so I move my focus onto the variation amongst exporting firms. I construct four measures– longitudinal distance, time difference, workhours overlap, and schoolhours overlap – each of which captures the temporal distance/closeness of a firm's average trading partner. A 1 standard deviation change in longitudinal distance causes a 0.12 standard deviation change in the proportion of women hired. Consider two destination countries like Canada and Germany, which are similarly far away from Brazil as the ship sails, but Germany's clock is five hours ahead of Brazil, while Canada is only a couple of hours behind on average. This extra time difference of 3 hours translates to firms trading with German partners employing 1.7 percentage point fewer women.

After showing the effect on the extensive margin of employment, I move onto the effect on the intensive margin of earnings. Using worker-level regressions, I find that trading partners' temporal distance does not affect men's earnings, but increases the

[8] See Craig and Mullan (2011) and Cowan, Jones, and Swigert (2023).

[9] See Martinelli, Beatriz Rosa, and Fernandes (2019).

[10] See Viapiana (2023) and the original report by the Fórum Brasileiro de Segurança Pública (2023).

[11] Exporting firms are about 6 times the size of domestic firms in Brazil.

[12] See Clerides, Lach, and Tybout (1998), Melitz (2003), and Schwarzer (2017).

gender earnings gap. Having trading partners 2 hours further away increases the gender gap in earnings by 0.84 percentage points. This explains more than 40% of the extra gap seen in exporting firms. Exporters' temporal distance leads to a 0.15 percentage point widening of the earnings gender gap in the whole Brazilian formal economy, which is an increase by 1.2%. This earnings gap could be the result of relatively more hours worked by men. I see a statistically significant but economically insignificant effect on the number of hours female employees are obligated to work every week– a less than 3 minutes increase (on a mean base of about 40 hours per week) with 2 more hours of time difference. Contractual wages and wage rates are also not affected– this leads me to conclude that the difference in earnings arises due to differences in overtime pay, commissions, and bonuses. Men more easily avail the opportunity to secure these payments which are above the basic salary that they are obligated to.

Schoolhours overlap, which is the overlap between Brazilian schoolhours and partner workhours, turns out to be the most important measure of temporal closeness, pointing towards the outsized importance of motherhood in shaping these results. The more this overlap, the more is work concentrated during schoolhours, when the demand for childcare is lowest. To better understand this mechanism, I consider the decision of new mothers to exit firms. Using a panel event study design, I find that new mothers in firms with temporally very far away partners are 2.6 percentage points more likely to exit these firms than new mothers in firms with very close partners. Temporal distance adds to the child penalties that mothers encounter. This illustrates how motherhood increases the impact of temporal distance by reducing the ability of mothers to work odd hours. Government and private provision of childcare during normal workhours would *not* help reduce the gaps due to temporal distance. Rather, cheap alternatives outside these hours or more equitable sharing of childcare responsibilities in the household should significantly reduce these gaps.

I also uncover heterogeneous effects on workers in different occupation categories. The female share of blue collar workers and the female share of managers in exporting firms are unaffected by temporal distance, while the female share amongst white collar workers is adversely affected by temporal distance– an extra 2 hours of time difference decreases the female share of white collar workers by 1.64 percentage points, while an extra 2 hours of schoolhours overlap increases it by 3.32 percentage points.

The Brazilian setting is interesting for a number of reasons. Studies on gender gaps focus relatively more on developed country contexts (often because of relative ease of data access and institutional knowledge), and not on middle-income countries, so gaining more insight in such a setting with a different institutional framework, economic reality, and socio-cultural norms is welcome. Gender disparity is relatively high in Brazil: the World Economic Forum's Global Gender Gap Report (2022) ranked Brazil 94 out of 146 countries. The gender gap in wages is about 24 percent in the formal sector (Ben Yahmed 2018), even with progressive labor laws that are worker- and women-friendly with mandated four-month paid maternity leaves and explicit provisions against discrimination in the workplace. As my strategy relies on the variation in trading partners of exporting firms, Brazil having a large, diverse, and robust foreign trade sector is especially helpful.

Related Literature

This paper contributes to a long line of work on gender gaps in economic outcomes, and is most closely related to the more recent literature that focuses on aspects of personnel economics and work arrangement like temporal flexibility, overwork, and the particular hours worked. ‘Flexibility’ can often be a confusing term as it does not specify who is being asked to be flexible: are the employers demanding flexibility from their employees or is it that employees have the freedom to choose their workhours? These are two starkly different scenarios. Simultaneously, both are different from the concept of workhour normality that I study in this paper. Flexibility has a dynamic aspect to it, whereby work schedules could change from time to time and there is uncertainty regarding the number or timing of worhours. My focus, however, is on known or systematic work during odd hours. Hence, I use the term ‘normal’ to mean the usual workhours.

Flabbi and Moro (2012) estimate a search model and show that women value workhour flexibility, with this having an impact on the wage distribution. Goldin (2014a) documents a positive correlation between flexibility requirements of occupations, convexity of wages (with respect to hours), and the gender wage gap. She finds that jobs in business and law demand greater temporal flexibility from employees and consequently have higher gender gaps than jobs in science and technology. Studying the flexibility offered by the new gig economy, Cook et al. (2019) show that female Uber drivers earn 7 pp less than male drivers, mostly due to differences in their experience and preferences over driving speed and where to work. Mas and Pallais (2017) find that while women do not tend to value flexible schedules, they do place a higher value on working from home and avoiding irregular work schedules, whereby workers cannot anticipate their work schedules in advance. In my paper, I study abnormal workhours induced by trade partners, which are not necessarily unanticipated changes to workers' schedules, and show its effects on the employment and earnings gaps in exporting firms. Rather, they could be known and expected by the workers if the trade relationships are stable, but would constitute working at odd hours.

Cortés and Pan (2019) find that highly skilled women are constrained by demands made on them for household production. When substitutes for their household production emerge, women are able to take advantage of the disproportionate rewards offered by overwork. In the same vein, Gicheva (2013), Erosa et al. (2022), and Wasserman (2023) find that constraints on the number of hours can explain some portion of the gender gap. Overwork could be correlated with the ability to work odd hours (workers may work during the normal workhours and continue working during abnormal hours). In fact, I show that this is the case– the difference in earnings between men and women due to temporal distance emerges because of overtime pay, bonuses, commissions, etc. Cha and Weeden (2014) find that the effect of overwork on the gender wage gap was “most pronounced in professional and managerial occupations, where long work hours are especially common and the norm of overwork is deeply embedded in organizational practices and occupational cultures.” When I consider heterogeneous effects of temporal distance on different occupation categories, I find that the employment gap widens with larger temporal distance for white collar workers, but the earnings gap widens for white collar workers and managers. These are the workers for whom synchronous communication and management are most important.

Cubas, Juhn, and Silos (2023) show that the gender gap is higher in jobs that require more coordinated work schedules, and that women (especially those with children) are penalized for missing work during peak hours due to household production demand. Abnormal workhours are precisely in the complement of these peak hours (8 am to 5 pm), and I show that even a reduced ability or preference for working during non-peak hours can adversely affect women's earnings. They estimate that if coordination needs are (counter-factually) limited to that of the lowest observed value (seen amongst healthcare support workers), then the within-occupation gender gap would halve. In my estimates, I find that reducing the time difference by 2 hours (from a mean of 2.7) would reduce the extra gender gap seen in exporting by 40%.

My paper bolsters the evidence provided by these earlier papers that show the importance of particular work arrangements. Not only does the number of hours supplied matter, but when the hours are supplied matters. In addition, I employ data from a large middle-income developing economy, while most others focus on developed country contexts. Moreover, many papers in this area focus on a particular set of occupations or sectors. On the other hand, my paper uses comprehensive employer-employee matched data across all sectors and occupations, focusing on exporting firms.

There is a vast literature on the motherhood penalty paid by working women. For example, using Danish data, Kleven, Landais, and Søgaard (2019) show that the birth of a child creates a long-run gender earnings gap of around 20 percent. Ciasullo and Uccioli (2023) find that regular schedules decreased the child penalty in hours worked by 14%. Ganguli, Hausmann, and Viarengo (2021) observe that women (in a large multinational law firm) are more likely to exit the firm citing family and work–life balance reasons, while men report leaving for career advancement. Albanese, Nieto Castro, and Tatsiramos (2022) show that new mothers are much more likely to give up non-local employment, and this drives the child penalty gap in employment. Pertold-Gebicka, Pertold, and Datta Gupta (2016) show that women increasingly switch from the more competitive private sector to the more family-friendly public sector after giving birth to their first child, and this is accompanied with a drop in wages. The event study analysis in my paper adds to these findings by demonstrating that new mothers switch away from firms with far away trade partners at higher rates than from firms with close trade partners and from domestic firms.

Another strand of literature in labor economics deals more generally with the sorting of workers across firms and occupations, and the effect that has on wage inequality between genders. Early work by Blau (1977) showed that firms paying higher wages had lower proportions of female workers, and women were concentrated in firms that paid lower wages to both men and women across all occupations. Using employer-employee matched data from Portugal, Card, Cardoso, and Kline (2015) also find that women are less likely to work at firms that pay higher premiums to either gender. This matches my findings in this paper – exporting firms pay a large premium but employ fewer women. My results can contextualize these findings by providing a concrete setting (exporting firms) and cause (abnormal workhours) for these gaps. I show that what matters is not just occupation and sectoral choice, but sorting across foreign-trading and domestic firms. Even amongst exporting firms, the temporal location of trading partners plays a role by inducing different demands on employees' workhours.

Further, this paper adds to the literature that examines the relationship between trade and inequality. Helpman et al. (2016) show that most wage inequality is within sectors and occupations and for observationally similar workers, and is driven by firm size and trade participation. Many other studies have documented the existence of an "exporter wage premium" and its effects on inequality.[13] I also find that Brazilian exporters pay a premium– 20 log points for men– but this premium is 2

[13] See, for example, Baumgarten (2013), Riker (2015), Ackah and Bofah (2019), and Egger et al. (2020).

percentage points smaller for women. In addition, the gender employment and earnings gaps are higher in exporting firms. Schmillen (2016) shows that such a premium exists only when firms export goods over a long distance. I show that even for firms exporting goods across the same distance, the temporal distance between firms and their trading partners has important impacts on the distribution of the exporter wage premium. In fact, back-of-the-envelope calculations show that temporal distance explains 42% of the smaller premium paid to women.

Juhn, Ujhelyi, and Villegas-Sanchez (2013) find that tariff reductions associated with the North American Free Trade Agreement improved the wages of Mexican blue collar women as more productive firms entered the export market and upgraded their technology. On the other side, mirroring these estimates, Hakobyan and McLaren (2017) find that NAFTA led to reduced wage growth for married blue-collar women in the US. In contrast, my results suggest that export promotion policies often followed by governments from around the world might lead to an unintended widening of the gap between men and women and the entrenchment of inequalities along gendered lines.

In the following section, I describe the data. Then, I present my strategy and results, starting with four stylized facts that motivate the study. The main results start with an examination of the effect of temporal distance on the extensive margin of employment, followed by its effect on the intensive margin of earnings and hours. Next, I consider the decision of new mothers to exit exporters with very far or very close exporters at differential rates. Then, I explore the heterogeneity of effects across blue collar workers, white collar workers, and managers. Section 4 contains more empirical results to ascertain the robustness of the findings, and section 5 concludes.

2 Data

In this section, I briefly describe the datasets used in the empirical analysis.

2.1 *RAIS*

I use Brazilian employer-employee matched data, the *Relação Anual de Informações Sociais* (*RAIS*), which covers the universe of formal sector firms and employees in Brazil for the years 2011 to 2018. It is based on annual reports made by firms about all employees on their payroll in the previous year. Firms may be heavily fined for non-compliance and employees' public wage supplements are based on this data, so both parties have an incentive to report accurate data. This results in high compliance.[14]

Each annual observation is at the worker-establishment-contract level and is identified by the worker's unique ID, the firm's tax-registration number (*Cadastro Nacional de Pessoas Jurídicas*, *CNPJ*), and the dates of joining and separation. The worker and firm IDs allow me to match them across years.[15] For each contract, there is information about the worker (age, gender, race, education, etc.), the firm (size, primary activity, municipality, etc.), and the employment relationship (contract type, average salary, occupation, contractual wage, contractual hours, leaves, joining, separation, etc.) I use *RAIS* data only

[14]The Brazilian labor ministry (*Ministério do Trabalho e Emprego*) estimated that *RAIS* covered over 97% of formal employees in 2011. (Vick 2017)

[15]I use firm, establishment, and employer interchangeably here, but a firm in *RAIS* can have multiple establishments, which refer to a specific workplace of the firm. By *RAIS'* definition, the analysis here is at the establishment-level.

from 2011 to 2018 because of the intersection with accessible export data and variable uniformity. I provide more details about the dataset and the variables I focus on in appendix A.1.

Note that this excludes the informal sector workers from my analysis. Around 40% of the Brazilian workforce is employed informally. Menezes-Filho, Muendler, and Ramey (2008) find that while more educated and more experienced workers are more likely to select into the Brazilian formal sector, there is no significant relation between gender or occupation and selection into formality. They also found little to no effect of selectivity into formality on their estimates of returns to education, occupation premia, and gender differences. Similarly, Carneiro and Henley (1998) find no effect of the size of the Brazilian informal sector on short-term formal sector labor market outcomes. This provides reassurance that the informal sector might not affect the estimates by a large degree, but the results here should be conservatively interpreted as solely pertaining to the formal sector.

Table 1: **Worker Summary Statistics by Gender**

	Men Mean/Std. Dev.	Women Mean/Std. Dev.	[Men] - [Women] Difference/p-value
Age	36.974	36.830	0.144***
	(11.975)	(11.549)	(0.000)
Prop. High School Graduate	0.698	0.823	-0.126***
	(0.459)	(0.381)	(0.000)
Prop. College Graduate	0.146	0.274	-0.127***
	(0.354)	(0.446)	(0.000)
Avg. Monthly Earnings (in BRL)	3010.981	2575.121	435.859***
	(4133.711)	(3510.562)	(0.000)
Avg. Monthly Earnings (Winsorized) (in BRL)	2931.866	2525.748	406.118***
	(3376.051)	(2870.903)	(0.000)
Monthly Contractual Salary (in BRL)	2359.021	2132.244	226.777***
	(21068.051)	(20775.450)	(0.000)
Hourly Contractual Wage Rate (in BRL)	15.520	15.995	-0.475***
	(154.821)	(169.487)	(0.000)
Contractual Hours (per week)	41.857	39.791	2.066***
	(5.355)	(7.257)	(0.000)
Number of Days of Leave/Absence	3.634	7.836	-4.202***
	(24.873)	(33.357)	(0.000)
Time Employed at Current Employer (in months)	58.374	63.359	-4.985***
	(81.630)	(84.521)	(0.000)
Prop. Working at Exporters	0.095	0.049	0.046***
	(0.293)	(0.215)	(0.000)
Prop. Blue Collar	0.492	0.224	0.268***
	(0.500)	(0.417)	(0.000)
Prop. White Collar	0.459	0.726	-0.266***
	(0.498)	(0.446)	(0.000)
Prop. Manager	0.049	0.051	-0.002***
	(0.216)	(0.219)	(0.000)
Observations	29787457	23466295	53253752

The sample consists of all workers in 2018 who earned a positive wage. P-values in the third column are from robust standard errors. Winsorized salaries are winsorized at the 1% level. ****** indicate significance at 10%\5%\1% levels, respectively.

Only contracts with a positive average salary are retained for analysis[16], leaving me with about 66 million observations in

[16]Following the approach in Menezes-Filho, Muendler, and Ramey (2008).

2018, representing 53 million workers employed in 3.33 million establishments (with similar numbers in past years aggregating to around 450 million observations for the period 2011 to 2018.) I present some summary statistics (grouped by gender) in table **??**. A few statistics stand out. Even though women are more educated on average (with higher proportions of both high school and college graduates), they earn less than men. There is a big gap in employment in exporting firms, with women 4.6 percentage points less likely to work there. Women also seem to take more leaves and work fewer hours per week.

2.2 Trade and Time Measures

Using their tax identification number (*CNPJ*), I match establishments with foreign trading status information for the respective year from the *Secretaria Comércio Exterior* (SECEX). So, a firm is considered an *Impex* firm if it is registered as an importer or an exporter; otherwise, it is considered *Domestic*. Establishment summary statistics (grouped by Impex status) in table **??**.

Table 2: **Establishment Summary Statistics by Exporting Status**

	Exporter Mean/Std. Dev.	Domestic Mean/Std. Dev.	[Exporter] - [Domestic] Difference/p-value
No. of Workers	71.273	11.657	-59.616***
	(236.373)	(275.529)	(0.000)
Prop. of Female Workers	0.317	0.469	0.151***
	(0.285)	(0.399)	(0.000)
Prop. of Blue Collar Workers who are Female	0.220	0.316	0.097***
	(0.289)	(0.402)	(0.000)
Prop. of White Collar Workers who are Female	0.365	0.556	0.191***
	(0.355)	(0.415)	(0.000)
Prop. of Managers who are Female	0.384	0.538	0.153***
	(0.300)	(0.405)	(0.000)
Observations	10020	3337431	3347451

The sample consists of all establishments in 2018 who employed at least 1 worker earning a positive wage. P-values in the third column are from robust standard errors. ****** indicate significance at 10%\5%\1% levels, respectively.

Table 3: **Coverage by Exporting Status (2018)**

	Domestic	Exporter	All
Municipalities	5570	2358	5570
Immediate Geographic Regions	510	466	510
Intermediate Geographic Regions	133	133	133
States	27	27	27
Activities	669	610	669
Municipio-Activity Pairs (SECEX)	-	7600	-

I use municipality-month-commodity level data from SECEX, which specifies the quantity (by weight) and value of goods exported to each foreign country. I aggregate the value of exports for each year to construct weights for each trading partner country: w_{mctp}, for municipality m exporting commodity c in year t to trading partner p. I use these weights to construct four measures, τ^{ℓ}_{mct} $(\ell = 1,2,3,4)$, for municipality-commodity pairs that each represent some notion of distance/closeness from their average trading partner. The further away a trading partner, the more abnormal workhours it would induce in the exporting firm. Ideally, this would be available at the establishment-level, but it is not to me, so for any exporting establishment e in municipality m selling commodity c at time t, I set $\tau^{\ell}_{et} = \tau^{\ell}_{mct}$, assigning the respective municipality-commodity's measure to the establishment. Note that this was not a trivial exercise as the firms' primary activity codes (*CNAE 2.0*) had to be matched to the commodity codes in the export data (4-digit Harmonized System), and the mapping between them is many-to-many. More details on the mapping procedure are presented in appendix A.2.

2.2.1 Longitudinal Distance (in degrees)

For any destination country p, the longitude of its population centroid[17] is used as the average longitude of the whole country, λ_p. Then, the longitudinal distance from country p for a municipality m is just the absolute difference between λ_p and λ_m, and the measure is calculated as $\tau_{mct} = \sum_p |\lambda_p - \lambda_m| w_{mctp}$. The range for this measure is from 0 to 180 degrees, and I present the distribution in figure A.2.1. An alternative would be to use the longitudinal distance from the country's closest port, as the exports are most likely to be headed there, but in the absence of precise knowledge about the partner firm in the destination country, the population centroid is the best guess for where it is located.

2.2.2 Timezone Difference (in hours)

The simple average of the timezones in effect in any destination country was used to calculate the difference from the timezone in effect in any municipality.[18] Then, the measure is calculated analogous to the longitudinal distance. The range is from 0 to 16 hours, and I present the distribution in figure A.2.1.

2.2.3 Workhours Overlap (in hours)

Unlike the first two measures which were distance measures, this is a measure of closeness. Assuming a 9-to-5 workday everywhere, the overlap in the workhours between the destination country and the municipality is calculated.[19] For example, Germany is 5 hours ahead of Rio de Janeiro. This induces a workhours overlap of 3 hours: 2PM to 5PM in Germany and 9AM to 12PM in Rio. For countries more than 8 hours away, the overlap would be 0. As the overlap increases, exporters would find it easier to work normal hours. I present the distribution in figure A.2.1.

2.2.4 Schoolhours Overlap (in hours)

Assuming that the schoolday ends in Brazil at 2PM and a 9-to-5 workday everywhere, the overlap between the Brazilian schoolhours and destination workhours at the destination are calculated.[20] The idea is that the time when children are usually in school is time that their parents can invest as they please. After these hours, some parents might need to pick up their kids or arrange childcare. This can add a constraint to their time after schoolhours, and they can be flexible with their time during

[17] Also called the gravitation center, it is the point in a country which minimizes the sum of squared distances for every resident.
[18] These timezones are assumed to be static, and shifts like daylight savings time are ignored.
[19] Differing office cultures and work times across countries are ignored.
[20] Brazilian schools typically end sometime between 1 and 3.

schoolhours to interface with their foreign partners. The range is from 0 to 5 hours, and I present the distribution in figure A.2.1.

3 Strategy and Results

3.1 Preliminary Facts

First, I present four stylized facts:

1. Impex establishments employ many more workers.
2. Impex establishments employ proportionally fewer female workers.
3. There exists an "impex premium".
4. The gender wage gap is wider in impex firms.

To ascertain the first two facts I run establishment-level regressions of the form (separately for each year):

$$y_e = \beta_0 + \beta_1 * Impex_e + GeoFE_g + LegalNatureFE_\ell + ActivityFE_a + \varepsilon \tag{1}$$

, where y_e is an outcome for establishment e, which is situated in immediate geographic region g, of legal nature ℓ, and conducts primary activity a. $Impex$ is a binary variable denoting the foreign trading status of the establishment and XFE are fixed effects for characteristic X. I also disaggregate the impex establishments into "Pure Importers" (importers who do not export), "Pure Exporters" (exporters who do not import), and "Importers and Exporters", and run analogous regressions; these results are in appendix B.1. The first dependent variable is the number of workers employed at an establishment at the end of the year. The second is the proportion of workers who are female. I weigh each observation in the latter regressions with the respective number of workers employed in each establishment. Estimates for the year 2011 (the first year in the sample) are presented here. Analogous figures for 2016 (instead of 2011), are presented in appendix B.2, with the estimates barely changing. The sample consists of all tax-registered establishments who paid a positive average salary to at least one employee during the year. There are 3,059,303 such establishments in 2011, employing 54,249,413 workers. Out of these, 45,647 (< 1.5%) are registered as impex firms, employing 8,334,501 workers (< 13%).

3.1.1 Impex establishments employ many more workers

This can be seen in Figures 1 and 12, which plot predicted levels of the number of workers employed at an establishment from regressions with fixed effects corresponding to the establishment's legal nature (1-digit), immediate geographic region, and primary activity (from left to right: sector, 3-digit, or 5-digit *CNAE 2.0* codes.)[21] Impex establishments employ about

[21] More details about the controls can be found in appendix A.1.

ten times as many people as domestic establishments. The coarseness of the activity fixed effects does not seem to matter. Some studies document a "large firm wage premium" (for example, Bloom et al. (2018) in the US, and Lochner, Seth, and Wolter (2020) in Germany), so it might be expected that impex firms, being larger, pay some sort of impex premium. This foreshadows the third stylized fact.

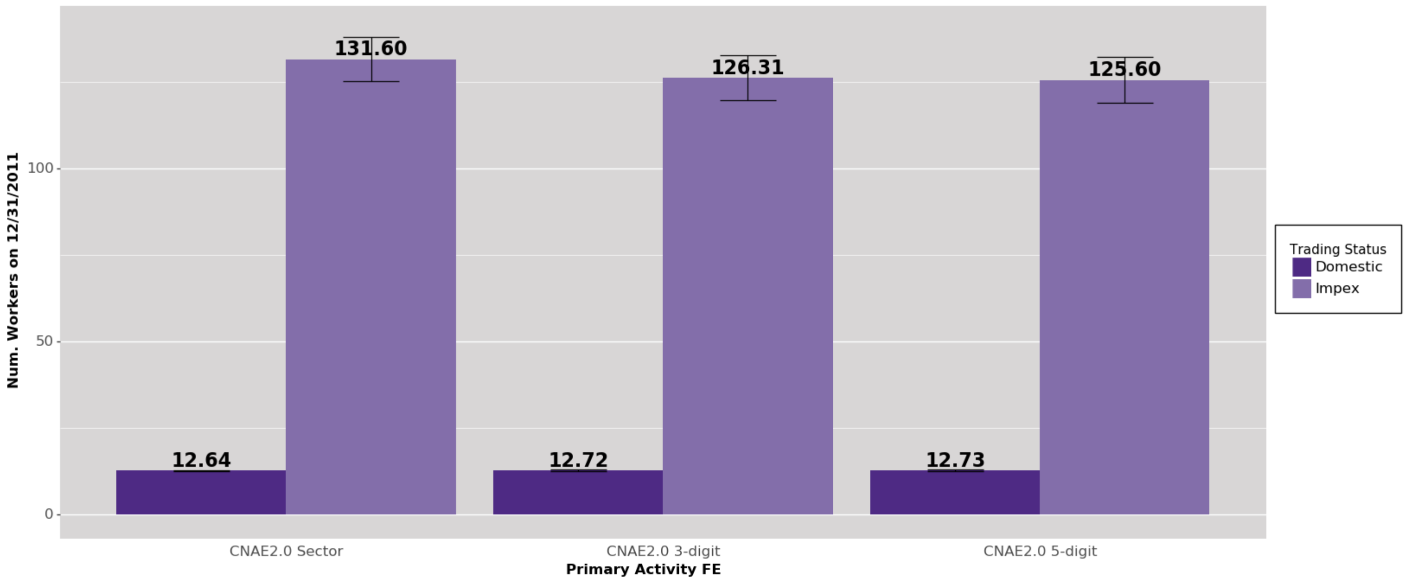

Figure 1: Impex Establishments Employ More Workers (2011)

3.1.2 Impex establishments employ proportionally fewer female workers

Figures 2 and 13 plot predicted levels of the proportion of female workers employed in an establishment using the same methodology used to establish the first fact. When using coarse sectoral controls, impex firms seem to employ about 5.2 percentage point fewer women. Using finer controls, the difference reduces to around 1.7 percentage points, suggesting that certain sectors are more/less conducive to female employment. What causes women to not choose (or be chosen by) impex firms? In section hypothesis is that workhour normality is a significant reason for this.

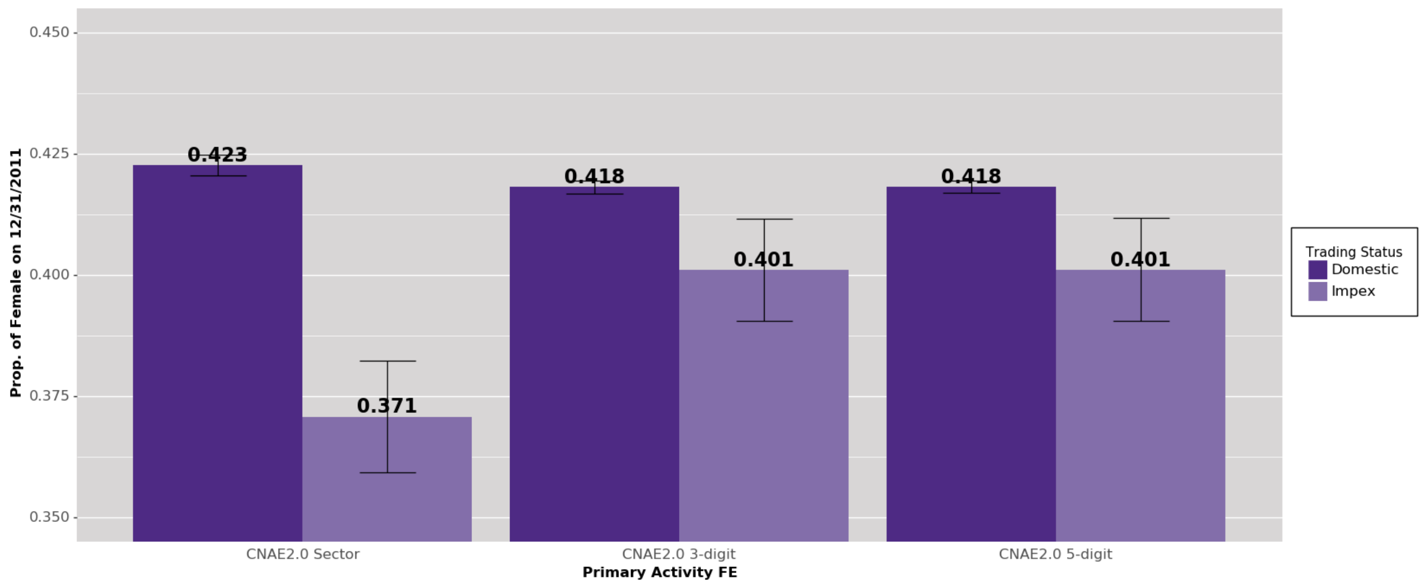

Figure 2: Impex Establishments Employ Proportionally Fewer Women (2011)

3.1.3 Impex establishments pay a premium and have a wider gender gap

The last two facts are established using worker-level regressions of the form:

$$log(earnings_{we}) = \beta_0 + \beta_1 * Impex_e + \beta_2 * Female_w + \beta_3 * Female_w * Impex_e + GeoFE_g + LegalNatureFE_\ell + \varepsilon \quad (2)$$

To this baseline specification, following the approach in Goldin (2014b), I progressively add:

1. Worker characteristic controls (age, education, and race fixed effects),
2. Primary activity (5-digit *CNAE 2.0*) fixed effects,
3. Occupation (4-digit *CBO2002*) fixed effects, and
4. Establishment size and worker tenure controls.

Figures 3 plots log differences in average salaries for men in impex firms, women in domestic firms, and men in impex firms, when compared to men in domestic firms.[22] Both men and women earn higher wages in impex firms: in the sparsest model, the difference is 44 log points for men and 33 log points for women. However, this impex premium reduces as we add more controls. The largest drop occurs when adding fine (5-digit) primary activity fixed effects, which suggests that the impex firms are clustered in certain higher paying sectors. Adding occupation fixed effects also reduces these gaps, which again suggests that impex firms might have differing labor demand for particular jobs. The possible existence of a "large firm wage premium" (documented in Bloom et al. (2018) and Lochner, Seth, and Wolter (2020)) suggests that the impex wage premium might be arising due to their larger size, as evidenced in the first stylized fact. Hence, in the last specification, I also control for the size

[22]The large number of observations (about 54 million in 2011) leads to minuscule standard errors, rendering them invisible in the figures.

of the establishment. This does not affect the estimates, with the densest specification showing an impex premium of 17 log points for men and 14 log points for women. Thus, the impex premium is significantly smaller for women.

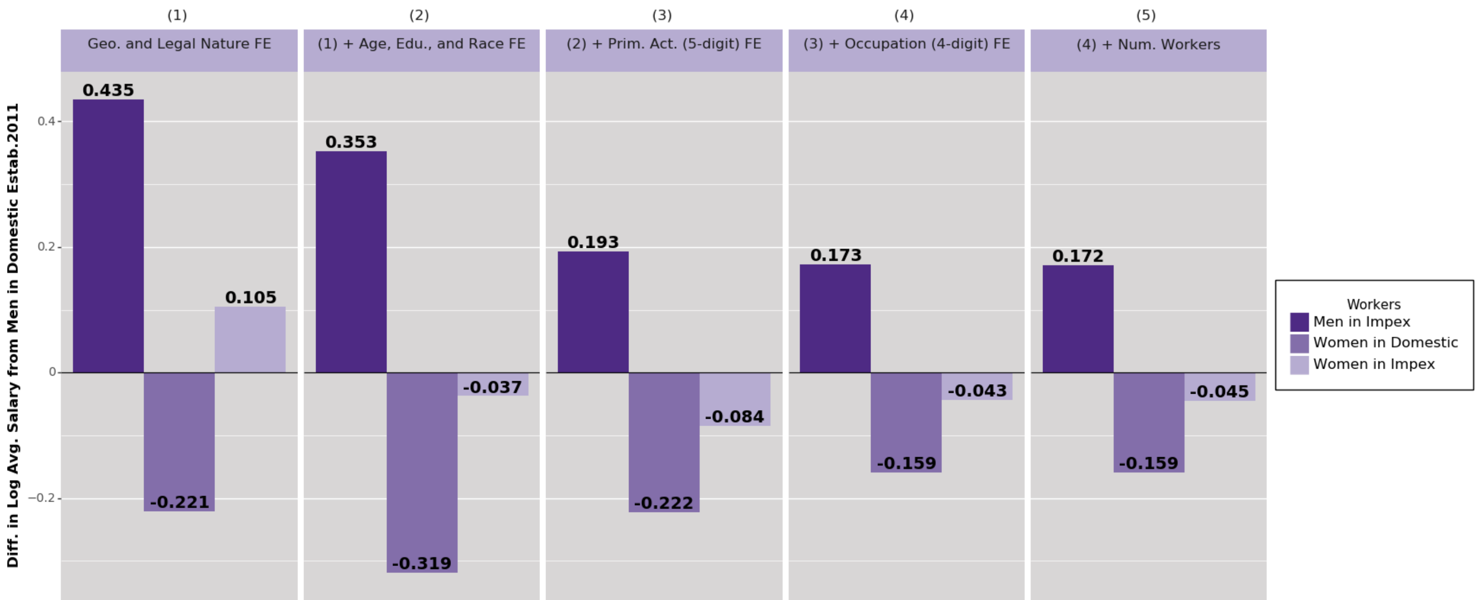

Figure 3: Impex Establishments Pay More (2011)

The gender gap exists in both domestic and impex firms, but it is much larger in impex firms: 23.2 percentage points compared to 17.2 pp. The larger impex gender gap completely offsets the impex premium, so that women in impex firms earn less than men in domestic firms. The larger impex gender gap can be more explicitly seen in Figures 4 and 14, wherein I plot the coefficients from the interaction term $Female * Impex$. Now, the largest drop in the gap occurs when I add the age, education and race fixed effects. The occupation fixed effects do not seem to matter. The gender gap is larger in impex firms by about 5.5 percentage points in the densest specification.

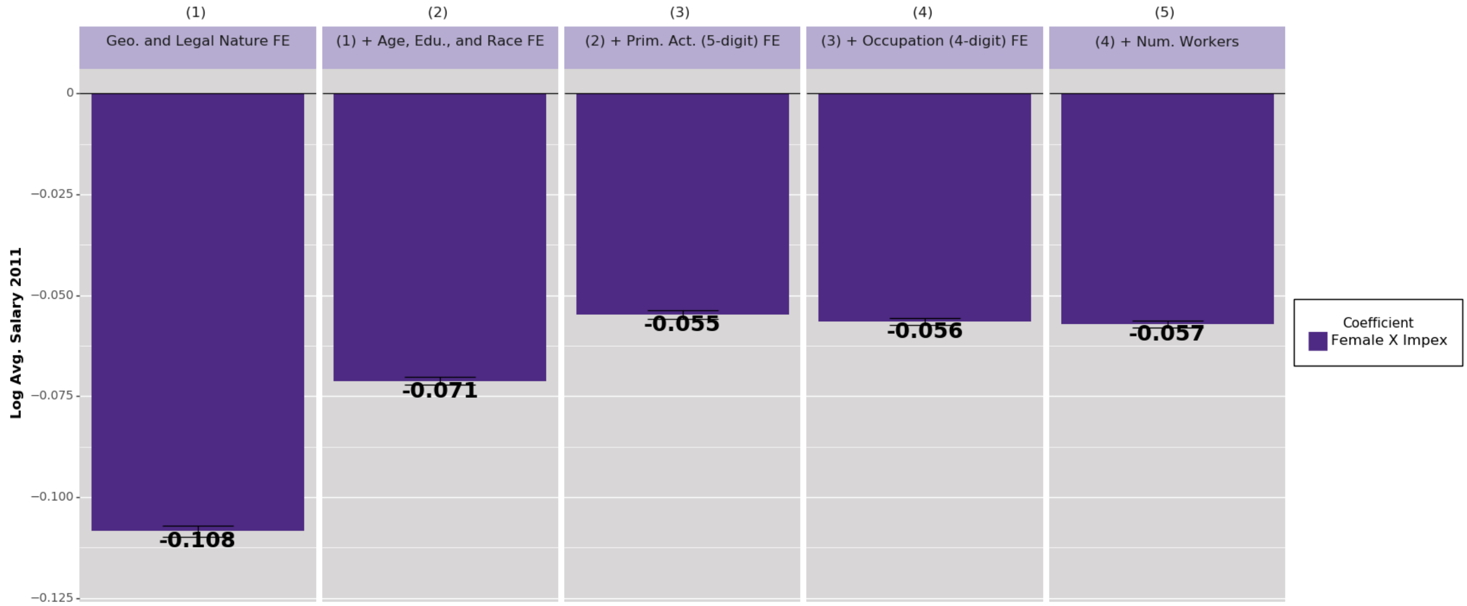

Figure 4: The Gender Gap is Higher in Impex Establishments (2011)

These stylized facts show that women's differential employment (extensive margin) and earnings (intensive margin) in impex firms explains some of the gender gaps we see in the wider economy. However, they might just be reflecting the effect of some unobserved factors. For example, it is well-documented that impex firms are usually more productive than domestic firms. More productive firms might self-select into exporting (Clerides, Lach, and Tybout 1998; Melitz 2003) and may even grow more productive through "learning-by-exporting" as they get access to new markets and partners ((De Loecker 2007; Atkin, Khandelwal, and Osman 2017). If higher productivity is correlated with a higher gender gap, it would not be the abnormal workhours in impex firms that cause the gaps, but their productivity. Thus, to lend more credence to the paper's central hypothesis, it becomes important to more closely examine these impex firms. In the rest of the paper, the analysis is restricted to *exporting* firms, and I use the time measures (elucidated upon in section 2.2) to ease out the effect of abnormal working hours on the gender gaps.

3.2 Effect of Temporal Distance: Selection

First, I compare establishments with temporally close foreign trading partners against those with temporally far-off trading partners. The further away the average partner, the more abnormal working hours will be demanded of the workers of the establishment. To see what effect this has on women's employment in exporting firms, I run the following establishment-level pooled regressions:

$$propfemale_{et} = \beta_0 + \beta_1 \tau_{et} + \gamma geodist_{et} + \Sigma_e + \phi_t + \varepsilon \tag{3}$$

, where $propfemale_{et}$ is the proportion of female workers in establishment e at time t, τ_{et} is one of the four time measures, $geodist$ is the average geodesic distance between the establishment and its trading partners, ϕ_t are year fixed effects, Σ_e are establishment-associated fixed effects (immediate geographic region and 3-digit activity). Each establishment is weighted by the number of workers working there. [23]

Consider two countries with very similar longitudinal distances from Brazil: Germany and Nigeria. Brazilian firms exporting the same product to Germany (9400 kms away) and those exporting to Nigeria (7000 kms away) would face, amongst other things, very different unit transport costs.[24] Extending the model in Melitz (2003) and considering heterogeneous transport costs to different countries based on distance, Holmes and J. J. Stevens (2012) show that larger and more productive firms will tend to export to more distant countries. Hence, conditioning on the average geodesic distance is quite important in this setting. Thus, the ideal comparison is between two firms in the same labor market selling the same commodity to two equidistant partners in different time zones.

To make the claim that these estimates are causal, firms' choice to export to certain countries have to be divorced from their labor market operations. More precisely, the identifying assumption is that unobserved differences between male and female workers are uncorrelated with firms' temporal distance to their trading partners. I think that this is a plausible assumption to make. There could be cases wherein the employment of a particular individual with connections to a partner country (through ethnic, cultural, or, linguistic closeness; or, with specialized knowledge of the regulatory framework; or, with direct business connections) might open new avenues of commerce for a firm. For example, Mion, Opromolla, and Sforza (2022) find that the presence of managers with prior experience in exporting to a particular market (Angola) doubles the probability of a firm entering that market following a positive exogenous shock (end of the Angolan Civil War.) There is, however, no reason to believe that these unobserved differences between employees would be along gendered lines.

I run regression equation 3 separately with each of the four time measures as the independent variable. The estimates of β_1 are presented in table 4, along with p-values derived from standard errors clustered at the municipality and 4-digit activity levels. This is the most appropriate level of clustering as the variation in the independent variable is at the municipality-activity level,[25] as I lack access to more granular firm-level export data. Labor market shocks should also be correlated within municipalities, while trade shocks would be similar for firms engaged in the same activity. The geographic and activity fixed effects are coarser than the level at which τ is assigned to allow for more variation to be exploited.

The coefficient for longitudinal distance is significant at the 5% level and tells us that for similar firms in the same labor market exporting the same products to equally distant similar countries, the one exporting to a country 1° longitude away would employ 0.00086 percentage points fewer women. Canada and Germany are roughly the same geodesic distance away (~9400 kms), but while Germany is about 40° away, Canada is only about 20° away. Thus, the extra temporal distance to Germany is 20° and then the estimate says that the proportion of female workers in firms exporting to Germany would be 1.72 pp less than in firms exporting to Canada.[26] This is quite a significant number, as the raw gap in employment between exporters and domestic firms is 15.1 percentage points. In standard deviation terms, a 1 standard deviation change in longitudinal distance

[23] *geodist* is calculated analogously to the longitudinal distance, and is explained in appendix A.2.

[24] Note that fixing the longitudinal distance does not fix the geodesic distance as there is latitudinal leeway.

[25] See Abadie et al. (2023) and MacKinnon, Nielsen, and Webb (2023).

[26] For comparison, the mean and standard deviation of longitudinal distance is 40.8 and 38.04, respectively.

Table 4: **Effect of Time Measures on Prop. of Workers who are Female**

Variable	(1)	(2)	(3)	(4)
Longitudinal Distance	−0.00086**			
	(0.01660)			
Time Difference		−0.00559*		
		(0.06167)		
Workhours Overlap			0.00273	
			(0.50888)	
Schoolhours Overlap				0.0133**
				(0.01063)
Weighted Observations	4,996,511	4,996,511	4,996,511	4,996,511
Degrees of Freedom	283	283	283	283
Establishment-related FE	Imm. Geo. Region, 3-digit Activity			
Other Controls	Firm Size, Geodesic Distance, Year FE			

Each column contains estimates from a separate establishment-level pooled regression. The sample consists of establishments which are exporters with at least 1 worker. The terms in parentheses are p-values from standard errors clustered at the Municipality and 4-digit Activity levels. ****** indicate significance at 10%\5%\1% levels, respectively.

leads to a 0.12 standard deviation change in the proportion of female workers in an establishment.[27] The coefficient for time difference is significant at the 10% level and paints a similar picture– 2 extra hours of time difference lead to a drop in the proportion of female workers by 1.2 percentage points.

Unlike the first two measures which are measures of distance, the last two time measures are measures of closeness. The coefficient for workhours overlap is statistically insignificant at the 10% level. The schoolhours overlap coefficient, which is significant at the 5% level, tells us that an extra 2 hours overlap in Brazilian schoolhours and destination workhours leads to a 2.66 pp *increase* in the proportion of female workers employed. Schoolhours overlap having a large impact might point us towards the mechanism through which workhour abnormality works, or at least the sub-group where it might be most salient: mothers. I return to this line of inquiry in section 3.4. But before that, I examine the effect that their trading partners have on the intensive margin for the firms' employees.

3.3 Effect of Temporal Distance: Earnings, Hours, Contractual Wage, and Wage Rate

In this section, I gauge any gendered impact that temporal distance to trading partners has on exporting firms' employees' outcomes, conditional on employment– in particular, their earnings, contractual wage, contractual hours, and contractual wage rate. To do so, I run worker-level pooled regressions of the form:

$$log(earnings_{wet}) = \beta_0 + \beta_1 Female_w + \beta_2 \tau_{et} + \beta_3 Female_w \times \tau_{et} + \gamma geodist_{et} + \omega K_w + \pi \Sigma_e + \rho \Psi_{we} + \phi_t + \varepsilon \tag{4}$$

, where $log(earnings_{wet})$ is the natural log of average monthly earnings of worker w in establishment e in year t, $Female_w$ is an indicator variable that equals 1 for women and is 0 otherwise, τ_{et} is one of the four time measures, $geodist$ is the average

[27]The mean and standard deviation of the proportion of female workers at exporting firms is 0.29 and 0.22, respectively.

Table 5: **Effect of Time Measures on log(Earnings)**

Variable	(1)	(2)	(3)	(4)
Female	−0.16574***	−0.16756***	−0.20609***	−0.21102***
	(0.00000)	(0.00000)	(0.00000)	(0.00000)
Longitudinal Distance	0.00009			
	(0.80213)			
Female x Longitudinal Distance	−0.00031*			
	(0.05277)			
Time Difference		0.00511		
		(0.14323)		
Female x Time Difference		−0.00419*		
		(0.07903)		
Workhours Overlap			0.00351	
			(0.31353)	
Female x Workhours Overlap			0.00494	
			(0.10152)	
Schoolhours Overlap				−0.00838
				(0.12010)
Female x Schoolhours Overlap				0.00909*
				(0.05452)
Observations	5,151,082	5,151,082	5,151,082	5,151,082
Degrees of Freedom	283	283	283	283
Worker-related FE	Age, Race, Education			
Establishment-related FE	Imm. Geo. Region, 3-digit Activity			
Job-related FE	Contract Type, 3-digit Occupation			
Other Controls	Firm Size, Tenure, Geodesic Distance, Year FE			

Each column contains estimates from a separate worker-level pooled regression. The sample consists of all workers at all exporters earning a positive wage. The terms in parentheses are p-values from standard errors clustered at the Municipality and 4-digit Activity levels. ****** indicate significance at 10%\5%\1% levels, respectively.

Table 6: **Effect of Time Measures on Hours**

Variable	(1)	(2)	(3)	(4)
Female	−0.13706***	−0.13354***	0.09553*	0.13844*
	(0.00000)	(0.00000)	(0.06597)	(0.05249)
Longitudinal Distance	−0.00224*			
	(0.07937)			
Female x Longitudinal Distance	0.00173***			
	(0.00130)			
Time Difference		−0.00549		
		(0.69353)		
Female x Time Difference		0.02544***		
		(0.00046)		
Workhours Overlap			−0.0017	
			(0.91191)	
Female x Workhours Overlap			−0.02907***	
			(0.00059)	
Schoolhours Overlap				0.01932
				(0.17067)
Female x Schoolhours Overlap				−0.05771***
				(0.00240)
Observations	5,151,082	5,151,082	5,151,082	5,151,082
Degrees of Freedom	283	283	283	283
Worker-related FE	Age, Race, Education			
Establishment-related FE	Imm. Geo. Region, 3-digit Activity			
Job-related FE	Contract Type, 3-digit Occupation			
Other Controls	Firm Size, Tenure, Geodesic Distance, Year FE			

Each column contains estimates from a separate worker-level pooled regression. The sample consists of all workers at all exporters earning a positive wage. The terms in parentheses are p-values from standard errors clustered at the Municipality and 4-digit Activity levels. ****** indicate significance at 10%\5%\1% levels, respectively.

geodesic distance between the establishment and its trading partners, K_w are a set of worker-associated fixed effects (age, education, and race), Σ_e are establishment-associated fixed effects (immediate geographic region, 3-digit activity, and legal nature), Ψ_{we} are job/contract-related controls (contract type and 3-digit occupation fixed effects, and tenure), and ϕ_t are year fixed effects.[28] The main coefficient of interest is β_3. Standard errors are clustered at the municipality and 4-digit activity levels as before. The results are presented in table 5.

Even conditional on the rich array of worker, establishment, and job-related controls, women earn 16 to 20 log point lower amounts than men, as shown by the coefficient for *Female* in table 5. The coefficients for the time measures represent the impact on men's earnings. These are all insignificant, except workhours overlap, which is significant at the 5% level, indicating that temporal distance does not affect the wages that men earn. The interaction terms are significant at the 10% level for all time measures with p-values sufficiently far away from 0.1, except workhours overlap. The interaction terms corresponding to the measures of distance (closeness) are negative (positive)– this means that further away partners lead to a widening of the gender gap in earnings within exporting firms. A 2 hour increase in time difference leads to a 0.84 percentage point increase in the earnings gender gap. The schoolhours overlap have an outsized impact– a 2 hour increase leads to a 1.8 percentage point decrease in the gap. As in the case of the extensive margin, this again indicates the importance of motherhood as a driver of

[28] $log(earnings_{wet})$ is winsorized at the 0.5 and 99.5 percentiles.

Table 7: **Effect of Time Measures on log(Contractual Wage)**

Variable	(1)	(2)	(3)	(4)
Female	−0.15459***	−0.15354***	−0.1465***	−0.15324***
	(0.00000)	(0.00000)	(0.00000)	(0.00001)
Longitudinal Distance	0.00212			
	(0.31547)			
Female x Longitudinal Distance	0.0001			
	(0.75598)			
Time Difference		0.03595		
		(0.16600)		
Female x Time Difference		0.00114		
		(0.81092)		
Workhours Overlap			−0.05445	
			(0.12240)	
Female x Workhours Overlap			−0.00067	
			(0.91101)	
Schoolhours Overlap				−0.05698*
				(0.08398)
Female x Schoolhours Overlap				0.00116
				(0.91287)
Observations	3,286,531	3,286,531	3,286,531	3,286,531
Degrees of Freedom	280	280	280	280
Worker-related FE	Age, Race, Education			
Establishment-related FE	Imm. Geo. Region, 3-digit Activity			
Job-related FE	Contract Type, 3-digit Occupation			
Other Controls	Firm Size, Tenure, Geodesic Distance, Year FE			

Each column contains estimates from a separate worker-level pooled regression. The sample consists of all workers at all exporters earning a positive wage. The terms in parentheses are p-values from standard errors clustered at the Municipality and 4-digit Activity levels. ****** indicate significance at 10%\5%\1% levels, respectively.

these effects.

This accounts for more than 40% of the extra gender earnings gap seen between exporting firms and domestic firms. Back-of-the-envelope calculations show that time difference amongst only exporters leads to a 0.15 percentage point widening of the earnings gender gap in the whole Brazilian formal economy, or an increase by 8.3%.

What is the cause of this widening of the gap? Men could be working longer hours in firms with larger temporal distances. In the *RAIS* dataset, I do not observe the actual number of hours worked by employees. However, I do observe the contractual hours– the number of weekly hours that an employee is contractually obligated to work for. Importantly, this does not include any overtime hours worked. Running the analog of regression equation 4 with contractual hours as the dependent variable, I obtain the estimates presented in table 6. Men's hours do not seem to be affected (only the coefficient for longitudinal distance is significant at the 10% level), while women's hours do seem to be, with all interaction term coefficients significant at the 5% level. However, the effect size is very small and economically insignificant. A 2 hour increase in time difference leads to women's hours *increasing* by 0.04 hours per week or 2 minutes and 24 seconds per week. This is less 0.1 percent of 44 hours per week, the contractual hours for more than 80% of the formal workforce in Brazil.[29]

The labor laws in Brazil limit weekly contractual hours to a maximum of 40 hours for those working five days a week

[29] See figure A.1.3.

Table 8: **Effect of Time Measures on log(Wage Rate)**

Variable	(1)	(2)	(3)	(4)
Female	−0.15044***	−0.14929***	−0.14918***	−0.15769***
	(0.00000)	(0.00000)	(0.00000)	(0.00000)
Longitudinal Distance	0.00206			
	(0.32707)			
Female x Longitudinal Distance	0.00005			
	(0.88047)			
Time Difference		0.0357		
		(0.16673)		
Female x Time Difference		0.00035		
		(0.94035)		
Workhours Overlap			−0.05415	
			(0.12054)	
Female x Workhours Overlap			0.0002	
			(0.97303)	
Schoolhours Overlap				−0.05775*
				(0.08504)
Female x Schoolhours Overlap				0.00305
				(0.77290)
Observations	3,286,531	3,286,531	3,286,531	3,286,531
Degrees of Freedom	280	280	280	280
Worker-related FE	Age, Race, Education			
Establishment-related FE	Imm. Geo. Region, 3-digit Activity			
Job-related FE	Contract Type, 3-digit Occupation			
Other Controls	Firm Size, Tenure, Geodesic Distance, Year FE			

Each column contains estimates from a separate worker-level pooled regression. The sample consists of all workers at all exporters earning a positive wage. The terms in parentheses are p-values from standard errors clustered at the Municipality and 4-digit Activity levels. ****** indicate significance at 10%\5%\1% levels, respectively.

and to 44 for those working six days.[30] This leads to there being very little variation in the contractual hours in the data, as evidenced in the histogram in figure A.1.3. It is possible (and plausible) that actual hours worked (contractual hours plus overtime) are quite different from these contractual hours, and that is where the difference could be seen. Even then, it is not clear in which direction we would see the effect of trading partners: firms with far-off trading partners might have a higher demand for overtime hours, and perhaps this demand is met mostly by men. At the same time, this might lead to the equilibrium actual hours worked by women to be higher than in other firms, albeit less than men.

In addition to the actual monthly earnings, the *RAIS* dataset has information on the basic wage contractually agreed to by workers and their employers. The difference between actual earnings and this contractual wage is comprised of overtime pay, tips, bonuses, commissions, etc. In anticipation of the heterogeneous ability of workers to work abnormal hours, firms might offer different contracts to different workers, as suggested by Goldin (2014a). Those who are able to work abnormal hours might be offered a higher contractual wage at a higher wage rate, with similar obligatory hours to be worked every week. To test this, I run the analog of regression equation 4 with $log(contractualwage)$ and $log(wagerate)$ as the dependent variables.[31] The estimates from these regressions are presented in tables 7 and 8, respectively.[32] In both sets of results, the coefficients for

[30] Further, employees cannot do more than 2 hours of overtime a day.
[31] The contractual wage rate is imputed by dividing the contractual wage by the contractual hours.
[32] The sample size falls as workers who are paid on a per-task basis are dropped, as their hourly wage rates cannot be ascertained.

the time measures and their interactions are all insignificant, except the coefficient for schoolhours overlap which is significant at the 10% level. Neither men's nor women's contractual wages or wage rates are affected by temporal distance.

Jointly, these results lead to the conclusion that the extra gender gap that arises in earnings is due to the portion that is not accounted by the contractual wage– tips, bonuses, commissions, overtime pay, etc. Temporally far away clients create a need for meetings to be attended and tasks to be performed outside the normal workhours. Men are more easily able to take up these tasks and the roles associated with them, and therefore, earn an outsized portion of overtime pay and any commissions that may arise from this work. Brazilian labor laws stipulate that overtime work be paid at 1.5 times the contractual wage rate, with the multiplier increasing to 2 on weekends and holidays. Thus, these results suggest that the difference is earnings is a result of men working *more hours* and at a *higher effective wage rate*.

In the next section, I proceed to examine what I consider the most salient mechanism through which workhour abnormality might hinder gender equity in the workplace: motherhood.

3.4 Maternity and Temporal Distance

One major reason why women tend to have a higher need for workhour normality is because of the uneven burden of household production that usually falls on them. Employed women in Brazil dedicate 73% more hours per week to caretaking and chores than employed men (18.1 hours vs. 10.5 hours.)[33] One major component of this is time spent on childcare; time-use surveys from across different countries and contexts have shown that mothers spend a disproportionate amount of time on child rearing.[34] Cowan, Jones, and Swigert (2023) show how mothers' schedules can revolve around their children's school schedules, while Buzard, Gee, and Stoddard (2023) find that school administrations tend to expect mothers to be the primary point of contact for their pupil's school-related communication. Daly and Groes (2017) show how mothers manage an overwhelming majority of their children's medical services, with social norms and economic considerations dictating this phenomena. These responsibilities can lead to women selecting out of establishments that require abnormal working hours. It is possible that motherhood leads them to quit their jobs with tough schedules at higher rates. I employ a panel event study design to tease out the importance of this mechanism.

The *RAIS* dataset does not contain information about workers' children and families, thus it is not possible to directly ascertain if and when a worker becomes a parent. Instead, I use information about leaves of absence. The number of days of leaves taken in the year are recorded in three separate tranches with the corresponding reasons (work accident, unrelated illness, maternity leave, unpaid leave, etc.) Using the reason for the leaves, I impute maternity status for women: a woman is said to have become a mother in year t if she took a maternity leave in year t.[35] Since, Brazilian labor laws mandate a strictly-enforced 120-day paid maternity leave (which can be extended to 180 days under some programs), the equivalence drawn between taking the leave and actual maternity is valid. However, this imputation means that women who might have become mothers prior to 2012 are not counted as mothers.[36] Hence, these results should be interpreted as the effect of an extra

[33] IBGE (2017)
[34] See Craig and Mullan (2011) and Pew (2015).
[35] In cases where the maternity leave might overflow into the next calendar year, only the first year is considered.
[36] The 2011 *RAIS* dataset does not have the reasons for leaves, so is ignored for these results.

child, and not the effect of the first child.

I divide women's job-contracts (worker-establishment-contract tuples) into 3 groups based on the trading status and time difference to trading partners: *domestic*, *very close exporters*, and *very far exporters*. Very close exporting jobs are job-contracts that remain below the 25th percentile of time difference throughout their tenure and very far exporting jobs are job-contracts that remain above the 75th percentile. [37] In my estimation sample, I keep all very close and very far exporting jobs, all domestic jobs during which the worker gave birth, and a 5% random sample of domestic jobs in which the worker did not give birth. Then, I run an panel event study regression of the form:

$$\begin{aligned}
separation_{wet} = \alpha &+ \sum_{j=1}^{6} \beta_{1j} Lead^{j}_{wt} + \sum_{k=0}^{6} \beta_{2k} Lag^{k}_{wt} \\
&+ \alpha_{vc} + \sum_{j=1}^{6} \beta_{3j} Lead^{j}_{wt} \times VCloseExporter_e + \sum_{k=0}^{6} \beta_{4k} Lag^{k}_{wt} \times VCloseExporter_e \\
&+ \alpha_{vf} + \sum_{j=1}^{6} \beta_{5j} Lead^{j}_{wt} \times VFarExporter_e + \sum_{k=0}^{6} \beta_{6k} Lag^{k}_{wt} \times VFarExporter_e \\
&+ \omega \cdot K_w + \pi \cdot \Sigma_e + \rho \cdot \Psi_{we} + \phi_t + \varepsilon \qquad (5)
\end{aligned}$$

, where $separation_{wet} = 1$ if worker w exited from establishment e in year t. $Lead^{j}_{wt} = 1$ if worker w became a mother in year $t+j$ and $Lag^{k} = 1$ if worker w became a mother in year $t-k$, and 0 otherwise. $VCloseExporter$ and $VFarExporter$ are binary variables indicating whether the worker was working at a *very close exporter* and *very far exporter*, respectively. K_w are a set of worker-associated fixed effects (age, education, and race), Σ_e are establishment-associated fixed effects (municipality, 3-digit activity, and legal nature), Ψ_{we} are employment-related controls (contract type fixed effects, 3-digit occupation fixed effects, and tenure), and ϕ_t are year fixed effects. Workers at domestic firms are the omitted category. Hence, for example, β_{4k} is the difference between the separation probabilities of mothers working in very close exporters and mothers working in domestic firms k years after giving birth, after differencing the separation probability of "never mothers" in domestic firms from the separation probability of "never mothers" in very close exporters.[38] That is:

$$\begin{aligned}
\beta_{4k} = \mathbb{E}[\text{ separation } k \text{ years after birth}|Mother, VCloseExporter] - \mathbb{E}[\text{separation } k \text{ years after birth}|Mother, Domestic] \\
-(\mathbb{E}[\text{separation}|NeverMother, VCloseExporter] - \mathbb{E}[\text{separation}|NeverMother, Domestic])
\end{aligned}$$

The estimates of $\beta_{3j}, \beta_{4k}, \beta_{5j}, \beta_{6k}$ $(j, k = 0, 1, \ldots, 6)$ are plotted in figure 3.4, while the numerical estimates are in table 9. In the post-motherhood period, the separation probabilities follow an ordered pattern: workers working at very close exporters are much more likely to exit than workers at very far exporters, and workers are much more likely to exit than The coefficients

[37] I also partition exporters above and below the median of time difference and run the analogous regression. These results are presented in section 4.2.

[38] Note that "never mothers" are women in our sample whom we do not observe taking a maternity leave between 2012 and 2018.

Table 9: **Effect of Motherhood on Separation**

Variable	Coefficient	95% Lower Conf. Limit	95% Upper Conf. Limit
6 Years before Birth × Very Close Exporter	−0.000121	−0.000481	0.000238
6 Years before Birth × Very Far Exporter	0.000520	0.000082	0.000958
5 Years before Birth × Very Close Exporter	0.000904	0.000572	0.001235
5 Years before Birth × Very Far Exporter	−0.000382	−0.000801	0.000037
4 Years before Birth × Very Close Exporter	0.000198	−0.000114	0.000510
4 Years before Birth × Very Far Exporter	0.000837	0.000446	0.001228
3 Years before Birth × Very Close Exporter	0.000032	−0.000255	0.000318
3 Years before Birth × Very Far Exporter	0.000099	−0.000262	0.000461
2 Years before Birth × Very Close Exporter	0.000658	0.000404	0.000912
2 Years before Birth × Very Far Exporter	0.000066	−0.000263	0.000396
1 Year before Birth × Very Close Exporter	−0.000391	−0.000610	−0.000171
1 Year before Birth × Very Far Exporter	0.000039	−0.000261	0.000339
Year of Birth × Very Close Exporter	0.047534	0.043716	0.051352
Year of Birth × Very Far Exporter	0.073580	0.068286	0.078874
1 Year after Birth × Very Close Exporter	0.031418	0.021068	0.041768
1 Year after Birth × Very Far Exporter	0.033604	0.024590	0.042618
2 Years after Birth × Very Close Exporter	0.038193	0.032481	0.043905
2 Years after Birth × Very Far Exporter	0.062143	0.053887	0.070399
3 Years after Birth × Very Close Exporter	0.043081	0.039727	0.046434
3 Years after Birth × Very Far Exporter	0.052775	0.045618	0.059931
4 Years after Birth × Very Close Exporter	0.020449	0.015166	0.025732
4 Years after Birth × Very Far Exporter	0.059986	0.047839	0.072133
5 Years after Birth × Very Close Exporter	0.015967	0.010830	0.021105
5 Years after Birth × Very Far Exporter	0.048531	0.037457	0.059605
6 Years after Birth × Very Close Exporter	0.014391	0.007083	0.021699
6 Years after Birth × Very Far Exporter	0.009489	−0.000095	0.019073
Observations		22,975,453	
Degrees of Freedom		233	
Worker-related FE		Age, Race, Education	
Establishment-related FE		Imm. Geo. Region, 3-digit Activity	
Job-related FE		Contract Type, 3-digit Occupation	
Other Controls		Firm Size, Tenure, Year FE	

The sample consists of all women at Very Close Exporters and Very Far Exporters, all mothers at Domestic jobs, and a 5% sample of women at domestic earning a positive wage. 95% confidence intervals are constructed using standard errors are clustered at the Municipality and 4-digit Activity levels.

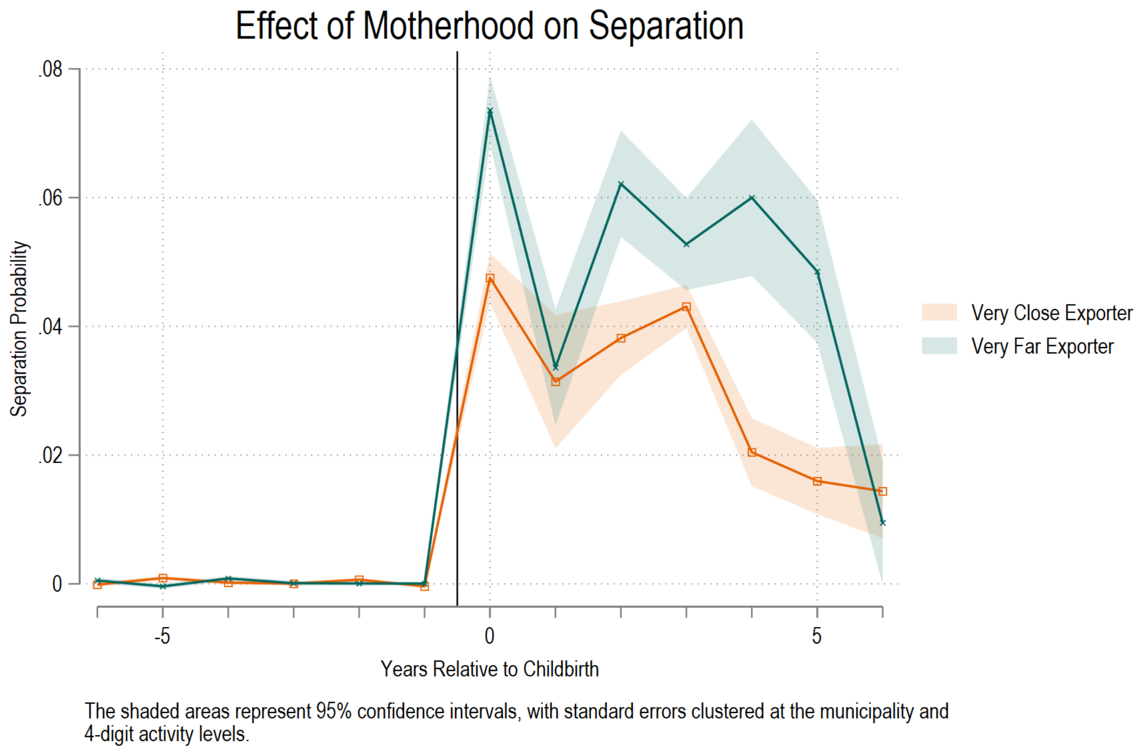

Figure 5: **Effect of Motherhood on Separation**

are significantly different at the 95% level for all post-motherhood years except 1 year and 6 years after birth. The difference becomes stark in the year of birth itself, as new mothers in very far exporters are 2.6 percentage points more likely to exit than new mothers in very close exporters ($\beta_{60} = 0.074, \beta_{40} = 0.048$). This is despite the mandatory paid maternity leaves in all firms, which might have helped retention. Employees on maternity leave are also protected from being dismissed without cause for the first five months after the birth. In the first year, many more women in very far exporters leave the firm either anticipating that they would be better off leaving or quickly learning this as they adjust to life with their child(ren). They anticipate or learn that their ability and/or preference to work abnormal hours is lower than what would be required to justify staying at the job. More women are pushed over this margin in very far exporters. One year after birth, the coefficients are statistically indistinguishable. However, the differences increase in year 2 and again from year 4 onwards, as new mothers in very far exporters start exiting their firms at higher rates, as children reach school-going age.

This shows that motherhood has a distinct effect on retention of female workers in very far exporting firms, illustrating an important mechanism through which the gender gap materializes on the extensive margin. This acts like another motherhood penalty: women's tenure at firms paying an export premium is interrupted at higher rates due to motherhood ($\beta_{4k}, \beta_{6k} > 0$), and that the penalty is higher in very far exporters ($\beta_{6k} - \beta_{4k} > 0$). This latter difference is more than half the difference between exit rates at domestic firms and very close exporters. These job interruptions have an adverse effect on workers' earnings as it pauses learning-on-the-job and gaining experience.[39] Sometimes promotion clocks can also be interrupted, limiting workers'

[39] See Bertrand, Goldin, and Katz (2010).

future promotion possibilities.

Fertility choice has been treated as exogenous to the place of employment of workers (specifically with respect to their temporal distance.) It is not implausible that fertility choices *are* affected by stringent workhour requirements at certain firms. In that case, the estimates shown here will systematically underestimate the true effect of workhour abnormality, as women adjust their fertility choices given their employers, and women with a greater ability or preference to work odd hours are the ones who remain at these firms. This acts as another constraint on women's decision-making ability.

In this next section, I discuss differential impact of temporal distance on different categories of workers– blue collar workers, white collar workers, and managers.

3.5 Heterogeneity by Occupation: Blue Collar Workers, White Collar Workers, and Managers

It is somewhat implausible that a factory-worker's workhours will be induced to change because of how far away a foreign importer is. What is far more likely is that employees who interface with the foreign clients regularly or manage teams that are required to work at odd hours are most affected by far away clients, who would induce abnormal workhours for them due to the demand for synchronous communication. To understand the differential impact of temporal distance on different occupational groups (blue collar workers, white collar workers, and managers),[40] the proportion of each group which is female is calculated for each establishment, and establishment-level pooled regressions of the following form are run for each group separately:

$$propfemale_{et}^{bc} = \beta_0 + \beta_1 \tau_{et} + \gamma geodist_{et} + \Sigma_e + \phi_t + \varepsilon \tag{6}$$

, where $propfemale_{et}^{bc}$ is the proportion of blue collar workers who are female in establishment e at time t, τ_{et} is one of the four time measures, $geodist_{et}$ is the average geodesic distance between the establishment and its trading partners, ϕ_t are year fixed effects, Σ_e are establishment-associated fixed effects (immediate geographic region, 3-digit activity, and legal nature). Each establishment is weighted by the number of the the group's workers working there. The estimates of β_1 are in tables 10, 11, and 12.

For the female proportion amongst blue collar workers (table 10), only the coefficient for longitudinal distance is significant at the 5% level, while the other three coefficients for the different measures of temporal distance/closeness are insignificant at the 10% level. This suggests that as temporal distance increases, the female share of blue collar workers is not affected. The corresponding coefficients in table 11 suggest that the situation is very different for white collar workers. As our intuition suggested, an increase in temporal distance decreases the female share of white collar workers. The coefficient for longitudinal distance is significant at the 5% level, while the coefficients for time difference and schoolhours overlap are significant at the 1% level. An extra 2 hours of time difference decreases the female share of white collar workers by 1.64 percentage points, while 2 extra hours of schoolhours overlap increases it by 3.32 percentage points. A 1 standard deviation change in the 3

[40]The workers are categorized following the procedure in Colonnelli, Prem, and Teso (2020).

Table 10: **Effect of Time Measures on Prop. of Blue Collar Workers who are Female**

Variable	(1)	(2)	(3)	(4)
Longitudinal Distance	−0.00091**			
	(0.02323)			
Time Difference		−0.00338		
		(0.36799)		
Workhours Overlap			0.00447	
			(0.25132)	
Schoolhours Overlap				0.00681
				(0.20473)
Weighted Observations	3,620,448	3,620,448	3,620,448	3,620,448
Degrees of Freedom	279	279	279	279
Establishment-related FE	Imm. Geo. Region, 3-digit Activity			
Other Controls	Firm Size, Geodesic Distance, Year FE			

Each column contains estimates from a separate establishment-level pooled regression. The sample consists of establishments which are exporters with at least 1 blue collar worker. The terms in parentheses are p-values from standard errors clustered at the Municipality and 4-digit Activity levels. ****** indicate significance at 10%\5%\1% levels, respectively.

Table 11: **Effect of Time Measures on Prop. of White Collar Workers who are Female**

Variable	(1)	(2)	(3)	(4)
Longitudinal Distance	−0.00108***			
	(0.00575)			
Time Difference		−0.0082**		
		(0.02406)		
Workhours Overlap			0.00369	
			(0.49369)	
Schoolhours Overlap				0.01659**
				(0.01109)
Weighted Observations	982,737	982,737	982,737	982,737
Degrees of Freedom	282	282	282	282
Establishment-related FE	Imm. Geo. Region, 3-digit Activity			
Other Controls	Firm Size, Geodesic Distance, Year FE			

Each column contains estimates from a separate establishment-level pooled regression. The sample consists of establishments which are exporters with at least 1 white collar worker. The terms in parentheses are p-values from standard errors clustered at the Municipality and 4-digit Activity levels. ****** indicate significance at 10%\5%\1% levels, respectively.

Table 12: **Effect of Time Measures on Prop. of Managers who are Female**

Variable	(1)	(2)	(3)	(4)
Longitudinal Distance	0.00033			
	(0.43259)			
Time Difference		0.00326		
		(0.39893)		
Workhours Overlap			0.00103	
			(0.83666)	
Schoolhours Overlap				−0.00034
				(0.94982)
Weighted Observations	170,130	170,130	170,130	170,130
Degrees of Freedom	275	275	275	275
Establishment-related FE	Imm. Geo. Region, 3-digit Activity			
Other Controls	Firm Size, Geodesic Distance, Year FE			

Each column contains estimates from a separate establishment-level pooled regression. The sample consists of establishments which are exporters with at least 1 manager. The terms in parentheses are p-values from standard errors clustered at the Municipality and 4-digit Activity levels. ****** indicate significance at 10%\5%\1% levels, respectively.

significant measures leads to a 0.13, 0.07, and 0.06 standard deviation change in the female share of white collar workers. Amongst managers, the female share is not significantly affected by temporal distance.

To understand the impact of time difference and schoolhours overlap on different occupational group's earnings, I run the following worker-level pooled regression:

$$\begin{aligned} log(earnings_{wet}) = &\beta_0 + \beta_1 Female_w + \beta_2 \tau_{et} + \beta_3 Female_w \times \tau_{et} \\ &+ \beta_4 WhiteCollar_{wet} + \beta_5 Female_w \times WhiteCollar_{wet} + \beta_6 \tau_{et} \times WhiteCollar_{wet} + \beta_3 Female_w \times \tau_{et} \times WhiteCollar_{wet} \\ &+ \beta_8 Manager_{wet} + \beta_1 Female_w \times Manager_{wet} + \beta_2 \tau_{et} \times Manager_{wet} + \beta_3 Female_w \times \tau_{et} \times Manager_{wet} \\ &+ \gamma geodist_{et} + \omega K_w + \pi \Sigma_e + \rho \Psi_{we} + \phi_t + \varepsilon \end{aligned} \tag{7}$$

, where $WhiteCollar$ and $Manager$ are indicators for membership in the respective occupational groups. Blue collar workers are the omitted category. The standard errors are clustered at the municipality and 4-digit activity levels. The coefficient estimates are presented in table **??**. Women in each occupational group earn less than men. The earnings of blue collar men are not affected by time difference, while blue collar women's wages *increase* with time difference. Time difference has a positive impact on male managers' earnings– 2 hours of extra time difference increases their earnings by 4.44 percentage points. The impact on women's earnings is muted by the negative triple-interaction coefficient of $Manager \times Female \times TimeDifference$. 2 extra hours of time difference increases female managers' earnings by only 2 percentage points– the gender gap amongst manager's increases by 1.2 percentage points as time difference increases.

The signs of the significant coefficients in schoolhours overlap (measure of temporal closeness) regression mirror the corresponding coefficients of time difference (measure of temporal distance). White collar women's earnings increase with schoolhours overlap. The size of the impact on the gender gap amongst managers is also similar– 2 hours of extra schoolhours overlap decreases the gap by 1.1 percentage points. While the effects of temporal distance on the extensive margin was seen only for white collar workers, the effects on earnings is seen for all groups– more distance is better for all women's earnings, however it worsens the earnings gap. Additional tables showing the impact on contractual hours, contractual wage and wage rate are presented in appendix D.

In the next section, I conduct a few exercises to test the robustness of my findings.

4 Robustness

In this section, I strive to get more precise estimates by making appropriate cuts in the data. First, I try to correct for the measurement error introduced when loosely assigning the time measures to establishments. Second, I compare new mothers' decision to exit firms with far away trading partners versus firms with close trading partners by partitioning exporters by the median of time difference (instead of comparing those above the 75th percentile against those below the 25th percentile of time difference.) Then, I show the effect of temporal distance on the proportion of female workers working in exporting

Table 13: **Effect of Time Measures on log(Earnings)**

Variable	(1)	(2)
Female	−0.15404***	−0.20926***
	(0.00000)	(0.00000)
Time Difference	0.00124	
	(0.72885)	
Female x Time Difference	0.00523**	
	(0.02134)	
White Collar	0.01397	−0.01934
	(0.50187)	(0.13351)
White Collar x Female	−0.02405**	0.01763
	(0.01029)	(0.30407)
White Collar x Time Difference	−0.00245	
	(0.25159)	
White Collar x Female x Time Difference	−0.00307	
	(0.11136)	
Manager	−0.01957	0.19813***
	(0.53819)	(0.00000)
Manager x Female	−0.16837***	−0.02259
	(0.00000)	(0.70485)
Manager x Time Difference	0.02228***	
	(0.00002)	
Manager x Female x Time Difference	−0.01231*	
	(0.08208)	
Schoolhours Overlap		−0.00492
		(0.33105)
Female x Schoolhours Overlap		−0.01139**
		(0.01231)
White Collar x Schoolhours Overlap		0.00768
		(0.14834)
White Collar x Female x Schoolhours Overlap		0.00963**
		(0.03091)
Manager x Schoolhours Overlap		−0.04388***
		(0.00000)
Manager x Female x Schoolhours Overlap		0.03274**
		(0.04146)
Observations	2,938,803	2,938,803
Degrees of Freedom	280	280
Worker-related FE	Age, Race, Education	
Establishment-related FE	Imm. Geo. Region, 3-digit Activity	
Job-related FE	Contract Type, 3-digit Occupation	
Other Controls	Firm Size, Tenure, Geodesic Distance, Year FE	

Each column contains estimates from a separate worker-level pooled regression. The sample consists of all workers at unique exporters earning a positive wage. The terms in parentheses are p-values from standard errors clustered at the Municipality and 4-digit Activity levels. ****** indicate significance at 10%\5%\1% levels, respectively.

Table 14: **Effect of Time Measures on Prop. of Workers who are Female**

Variable	(1)	(2)	(3)	(4)
Longitudinal Distance	−0.0007*			
	(0.06955)			
Time Difference		−0.00449		
		(0.11251)		
Workhours Overlap			0.00171	
			(0.61411)	
Schoolhours Overlap				0.01049**
				(0.03807)
Weighted Observations	2,921,631	2,921,631	2,921,631	2,921,631
Degrees of Freedom	280	280	280	280
Establishment-related FE	Imm. Geo. Region, 3-digit Activity			
Other Controls	Firm Size, Geodesic Distance, Year FE			

Each column contains estimates from a separate establishment-level pooled regression. The sample consists of establishments which are unique exporters with at least 1 worker. The terms in parentheses are p-values from standard errors clustered at the Municipality and 4-digit Activity levels. ****** indicate significance at 10%\5%\1% levels, respectively.

firms using an alternative specification with firm fixed effects. Finally, I discuss the use of finer controls in my regressions. Additional robustness exercises are presented in appendix C with additional tables in appendix D.

4.1 Unique Exporters

Not having access to firm-level export data, I rely on municipality-activity level data. Thus, I lose significant granularity when assigning my main explanatory variables (the 4 time measures) and introduce noise into estimation results. To account for this, I focus on municipality-activity pairs that are associated with a single unique exporter in a given year. Being the only exporter engaged in the activity in the municipality, the exports of the related products from the municipality in that year must originate from it. Thus, the time measures would be only assigned to the correct establishments. Doing this leads to a sample of 11,646 establishments (down from 24,323) employing 4,890,053 workers (down from 8,017,564), thus essentially halving the sample. So while precision is improved, I lose power due to a loss in sample size.

Next, regression equation 4 is re-run for this sample and the results are in table **??** The coefficients of the interaction terms are all significant at the 1% level, with their magnitudes all larger than for the full sample (table **??**). This hints towards this sub-sample somewhat solving the problem of attenuation bias arising from the measurement error that is introduced in the full sample.

4.2 Close vs Far Exporters

Instead of comparing exporting below the 25th percentile of time difference and above the 75th percentile (very close vs. very far exporters), in this robustness check I compare exporters below and above the median of time difference (2.83). I run the analog of the event study regression equation 5, and present the corresponding graph in figure 4.2 and the corresponding numerical estimates in table 9 in appendix section D. The effects are similar to what was seen for very far and very close exporters.

Table 15: **Effect of Time Measures on log(Earnings)**

Variable	(1)	(2)	(3)	(4)
Female	−0.16409***	−0.16553***	−0.20703***	−0.20903***
	(0.00000)	(0.00000)	(0.00000)	(0.00000)
Longitudinal Distance	−0.00026			
	(0.57238)			
Female x Longitudinal Distance	−0.00031*			
	(0.06059)			
Time Difference		0.00176		
		(0.64205)		
Female x Time Difference		−0.00426*		
		(0.07702)		
Workhours Overlap			0.00804**	
			(0.03987)	
Female x Workhours Overlap			0.00555*	
			(0.05638)	
Schoolhours Overlap				−0.00599
				(0.26292)
Female x Schoolhours Overlap				0.00884*
				(0.07769)
Observations	3,048,645	3,048,645	3,048,645	3,048,645
Degrees of Freedom	280	280	280	280
Worker-related FE	Age, Race, Education			
Establishment-related FE	Imm. Geo. Region, 3-digit Activity			
Job-related FE	Contract Type, 3-digit Occupation			
Other Controls	Firm Size, Tenure, Geodesic Distance, Year FE			

Each column contains estimates from a separate worker-level pooled regression. The sample consists of all workers at unique exporters earning a positive wage. The terms in parentheses are p-values from standard errors clustered at the Municipality and 4-digit Activity levels. ****** indicate significance at 10%\5%\1% levels, respectively.

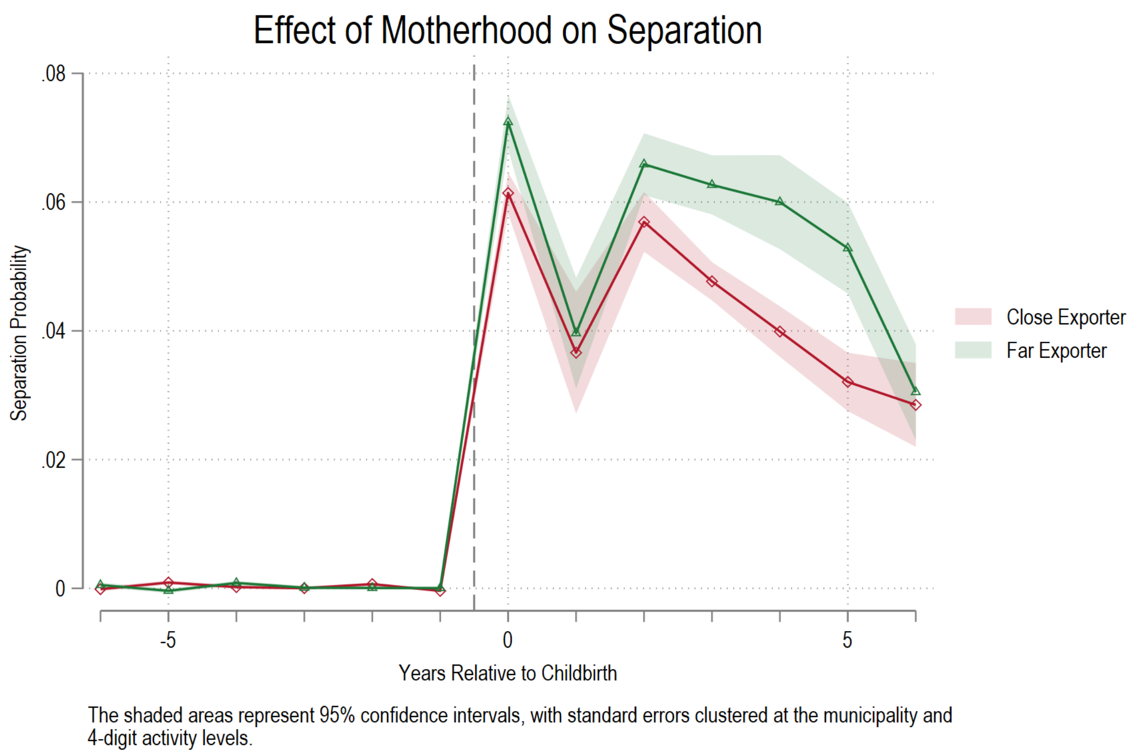

Figure 6: **Effect of Motherhood on Separation**

4.3 Firm Fixed Effects

To alleviate further concerns about unobserved firm heterogeneity, using only the intra-firm variation in the measures of time difference, I run fixed effect regressions of the form:

$$propfemale_{et} = \beta_1 \tau_{et} + \gamma geodist_{et} + \phi_t + \pi_e + \varepsilon \tag{8}$$

, where ϕ_t and π_e are year and establishment fixed effects, respectively. The results are presented in table 19 in appendix D.

None of the coefficients are significant with clustered standard errors. This could be due to a number of (mutually non-exclusive) reasons. These regressions only exploit the intra-firm variation in trading partners' distance/closeness across years. For the time measures, the within-firm variation is about one-third of the between-firm variation. Another reason why we do not find an effect could be that the changes induced within a firm due to different trading partners take time to come into effect.

4.4 Finer Controls

There is some leeway in which level of controls I can use:

- There are 4 levels of geographic controls that I could potentially use: states (27), intermediate geographic regions (133), immediate geographic regions (510), and municipalities (5570). States seem too loose, so are never used. Other than regressions which explicitly call for municipality fixed effects, the choice between the intermediate and immediate geographic regions does not seem to matter.

- In alternative regressions I use either sectoral fixed effects (21), 3-digit fixed effects (285), or 5-digit fixed effects (673). The sectoral classification often seems too crude, but estimates do not really change when going from the 3-digit fixed effects to the 5-digit fixed effects.
- The Brazilian Classification of Occupations (*CBO 2002*) codifies workers' occupations using 6-digit codes (2646), 4-digit codes (620), 3-digit codes (193), etc. In the worker-level regressions, I usually use the 4-digit codes, but 6-digit codes lead to similar estimates.

5 Conclusion

The estimation exercises undertaken in this paper show that abnormal workhours are an important determinant of gender gaps in employment and earnings. Brazilian exporting firms' temporal distance from their foreign trading partners induces different demands for work outside normal hours, and as this temporal distance increases, the worse the gender gaps get. On the extensive margin, two extra hours of time difference of an exporter from their trading partners leads to a decrease in the proportion of female employees by 1.2 percentage points. This represents 26% of the employment gap that exists between domestic and exporting firms. On the intensive margin, I find that having trading partners two hours further away increases the gender gap in earnings by 0.84 percentage points. This explains 42% of the extra gap seen in exporting firms. These results help me answer the motivating stylized facts about exporting firms and the gender gaps– why exporting firms employ a lower proportion of women, why they pay a smaller "exporter premium" to women workers, and why they exhibit a higher earnings gap.

Back-of-the-envelope calculations show that exporters' temporal distance leads to a 0.15 percentage point widening of the gender earnings gap in the whole Brazilian formal economy, which is an increase of 1.2%. Note that this is the impact of abnormal workhours just amongst exporters, who employ less than 10% of the formal workforce. If the effect of abnormal workhours is similar in a significant chunk of domestic firms, then the overall impact of abnormal workhours on the gender earnings gap would be much greater.

I also find that workers' contractual wages and wage rates are not affected by temporal distance, while contractual hours are only marginally affected. This helps me conclude that the difference in earnings arises due to differences in overtime pay, commissions, and bonuses. Men more easily avail the opportunity to secure these payments which are over and above the basic salary that they are obligated to.

Not all occupation groups are similarly affected. Temporal distance worsens the earnings gap amongst white collar workers and managers, but not amongst blue collar workers, emphasizing that temporal distance matters because of its impact on synchronous communication and management. The female share of blue collar workers and managers is also not affected; only the female share of white collar workers decreases as temporal distance increases.

In my analysis, I construct and use four measures of temporal distance/closeness– longitudinal distance, time difference, workhours overlap, and schoolhours overlap. The last of these, which is the overlap between Brazilian schoolhours and trade partner workhours, is the measure that is most potent in its impact on the gender gaps in employment and earnings. Using a panel event study design, I also find that new mothers are 2.6 percentage points more likely to leave exporting firms with far away trading partners than they are to leave domestic firms within a year of giving birth. These results point towards the outsized importance of motherhood in transmitting the effect of temporal distance– new mothers face tighter constraints on their time and their ability to work odd hours is reduced. Thus, temporal distance adds to the child penalties that mothers encounter by increasing their career interruptions.

The policy implications of these findings are nuanced. Mandated paid maternity leaves of four to six months are not enough to retain new mothers in the firms paying an export premium. Government and private provision of childcare during normal workhours would *not* help reduce the gaps due to temporal distance. Rather, cheap alternatives outside these hours or more equitable sharing of childcare responsibilities in the household could significantly reduce these gaps by reducing career interruptions for mothers, and hence, allow them to enjoy higher earnings throughout their career trajectories, and thus significantly reduce the gender gaps. The governments of developing countries often employ export promotion policies to escape the lower end of the world income distribution. If such policies encourage more international trade and increase the temporal distance of exporting firms, they might lead to an unintended widening of the gap between men and women and the entrenchment of inequalities along gendered lines.

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Appendix

A Data

A.1 *RAIS*

In this subsection I provide details about the variables used in my analysis, with some statistics for the year 2011, the first year in my sample.

A.1.1 Worker-related variables

1. Worker ID: Workers are identified using their unique registration number in the *Programa de Integração Social* (*PIS*) registry, which is used to administer public wage supplements and social security programs like unemployment insurance, child benefits, etc. This allows matching across firms and years.

2. Age (in years)

3. Race: In 2011, 0.2% workers identify as Indigenous, 48.8% as White, 4.4% as Black, 0.6% as East Asian, 26.1% as *Parda* (mixed). Race is unidentified for a fifth of the workers.

4. Education: Measured by a worker's final attainment, that is, whether they completed elementary school (4.2%), primary school (13.3%), high school (43.9%), undergraduate college (13.2%), master's degree (0.2%), or a PhD (0.08%).

A.1.2 Establishment-related variables

1. Establishment ID: Each establishment is identified by its registration number in the *Cadastro Nacional de Pessoas Jurídicas* (*CNPJ*), the National Registry of Legal Entities.

2. Legal Nature: According to the (1-digit) legal nature code, an establishment can be characterized as a public administration entity (0.7%), a business entity (91.7%), a non-profit (7.4%), an "individual" (0.3%), or an extraterritorial institution (0.01%).

3. Location: There are 4 levels of geographic identifiers for each establishment: state (27), intermediate geographic region (133), immediate geographic region (510), and municipality (5570). According to the Brazilian Institute of Geography and Statistics (*IBGE*): "Immediate Geographic Areas [...] are organized around nearby urban centers that can be accessed for the satisfaction of immediate needs of populations, such as: purchase of consumer goods, job search, health and education services and rendering of public services". Thus, the immediate geographic regions most closely correspond to the commuting zones often used in other contexts.

4. Primary Activity: Each establishment's primary activity is classified according to the National Classification of Economic Activities (*CNAE 2.0*). There are 21 sectoral codes, 285 3-digit codes, and 673 5-digit codes.

5. Establishment size: While *RAIS* has a coarse categorical variable for establishment size, I impute it using the number of workers employed at an establishment at the end of the given year.

A.1.3 Employment-related variables

1. Earnings: The mean monthly salary for the year is reported, regardless of the frequency of payments. Payments are considered part of the salary if they are taxable income or are subject to Brazilian social security contributions, including tips, commissions and fees, overtime earnings, hazard pay, bonuses, etc. I use the natural log of the average monthly salary as the earnings measure, with 0.5% winsorization at both the ends.

2. Contractual Wage: The basic salary contained in the employment contract. Importantly, unlike earnings this does not include tips, commissions and fees, overtime earnings, hazard pay, bonuses, etc. This basic salary is paid with different frequencies to employees– weekly, daily, monthly, per task, etc. I standardize it to the monthly level for all employees except those who are paid on a per-task basis, and use the natural log, with 0.5% winsorization at both the ends.

3. Contractual Hours: This is the number of weekly hours employees are contractually obligated to work for. This does not include any overtime hours. The distribution is shown in A.1.3.

4. (Contractual) Wage Rate: The contractual wage is divided by (monthly) contractual hours to obtain the (contractual) wage rate. The actual wage rate remains unobserved as I do not observe the actual number of hours worked.

5. Contract Type: Records whether the contract is fixed term or an indefinite period, and the type of worker (rural/urban/civil) and employer (corporate/individual/government.)

6. Leaves: The number of days of leaves taken in the year are recorded in three separate tranches with the corresponding reasons (work accident, unrelated illness, maternity leave, unpaid leave.) Using the reason for the leaves, I impute maternity status for women: a woman is said to have become a mother in year t if she took a maternity leave in year t. In cases where the maternity leave might overflow into the next calendar year, only the first year is considered. Since, Brazilian labor laws mandate a strictly-enforced 120-day paid maternity leave (which can be extended to 180 days under some programs), the equivalence drawn between taking the leave and actual maternity is valid.

7. Joining and separation: Along with the dates of admission and separation (if the employee has left the establishment), the reasons for their entry (transfer from within the firm, new hire, re-joined etc.) and exit (end of contract, firing, retirement, etc.) is also recorded.

8. Occupation: *Classificação Brasileira de Ocupações* (*CBO 2002*) codifies workers' occupations using 6-digit codes (2646), 4-digit codes (620), 3-digit codes (193), etc. In most worker-level specifications, I use the 4-digit codes. Blue collar workers, white collar workers, and managers are identified using the procedure in Colonnelli, Prem, and Teso (2020). This involves mapping the CBO 2002 codes to older CBO 1994 codes, and then using the concordance *cbo2isco*

provided by Marc-Andreas Muendler.[41]

In some robustness exercises, I also test the impact on occupations which might be most affected by abnormal workhours induced by foreign clients as they interface with them the most. I classify the following 3-digit *CBO 2002* codes as 'relevant':

(a) 121: General Directors

(b) 252: Organization and Business Administration Professionals

(c) 253: Public Relations, Advertising, Marketing and Commercialization Professionals

(d) 261: Communication and Information Professionals

(e) 352: Inspection, Supervision and Administrative Coordination Techniques

(f) 353: Medium-level Technicians in Financial Operations

(g) 354: Medium Level Technicians in Commercial Operations

(h) 410: Administrative Services Supervisors (Except Public Service)

(i) 411: Offices in general, Agents, Assistants and Administrative Assistants

(j) 412: Expedient Secretaries and Office Machine Operators

(k) 413: Accounting and Finance Offices

(l) 423: Dispatchers

(m) 510: Service Supervisors

(n) 520: Sales and Service Supervisors

(o) 521: Sellers and Demonstrators

(p) 522: Trade Repositories and Remarkers

A.2 Trade and Time Measures

The geodesic distance is calculated for each municipality-commodity pair by taking the average of the geodesic distance between the municipality and the geographic centroid of each destination country, weighted by the value of the exports to that country. Then, like the time measures, all establishments in the municipality engaged in the same activity are assigned the same geodesic distance.

[41]This concordance is available at http://econ.ucsd.edu/muendler/brazil.

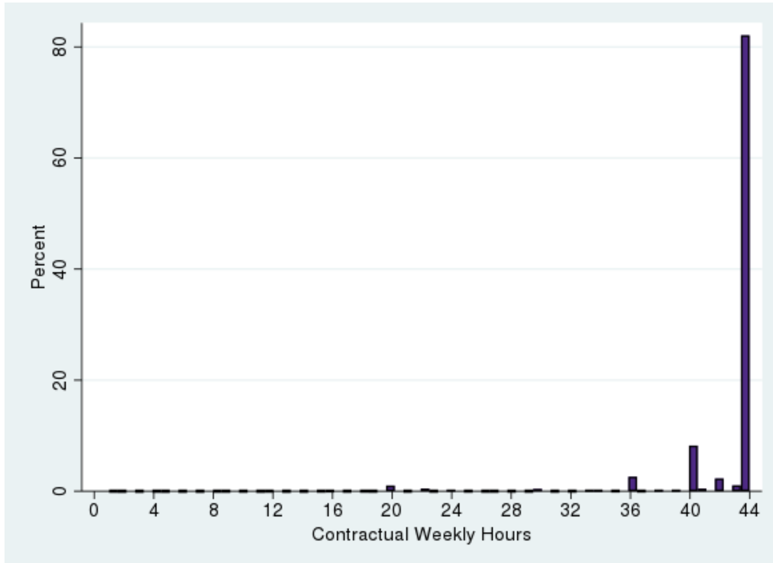

Figure 7: Histogram of Contractual Hours (2018)

A.2.1 Matching activities and commodities

The export commodities in the *SECEX* dataset are defined by their 4-digit Harmonized System codes. The establishments' activities are defined by their 5-digit *CNAE 2.0* activity codes. *SECEX* provides a *HS*-to-*CNAE* matching file. However, usually, a commodity is associated with several different 5-digit activity codes, and each activity code is associated with several different commodities. To simplify things, even if there exist competing claims for a commodity from different activities, I assign the exported value of the commodity to *all* activities it is associated with.

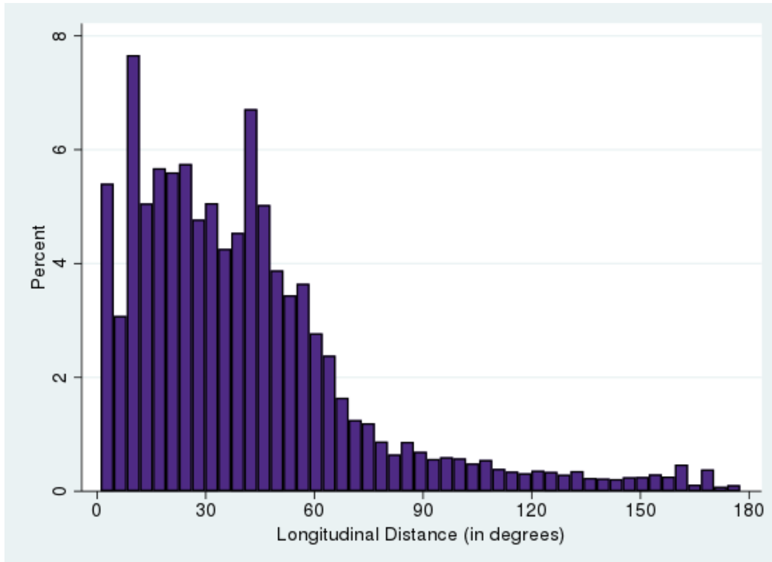

Figure 8: Distribution of Longitudinal Distance for Municipality-Activity Pairs (2011-2018)

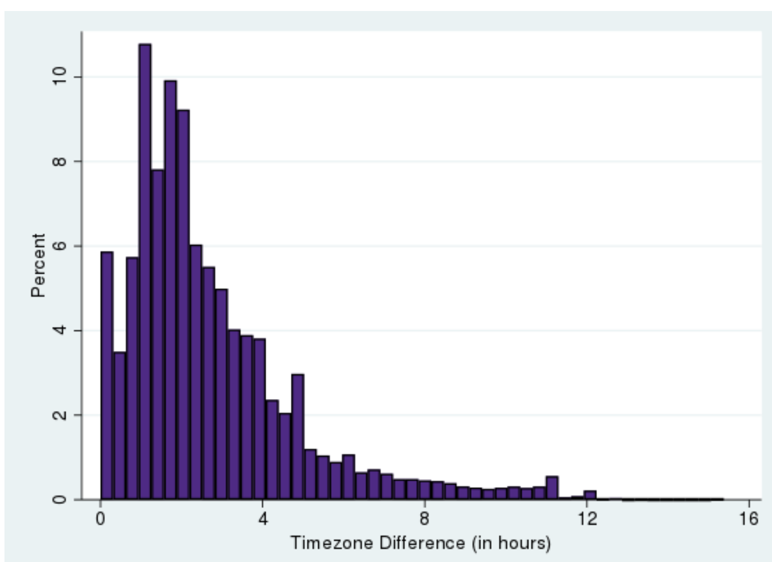

Figure 9: Distribution of Time Difference for Municipality-Activity Pairs (2011-2018)

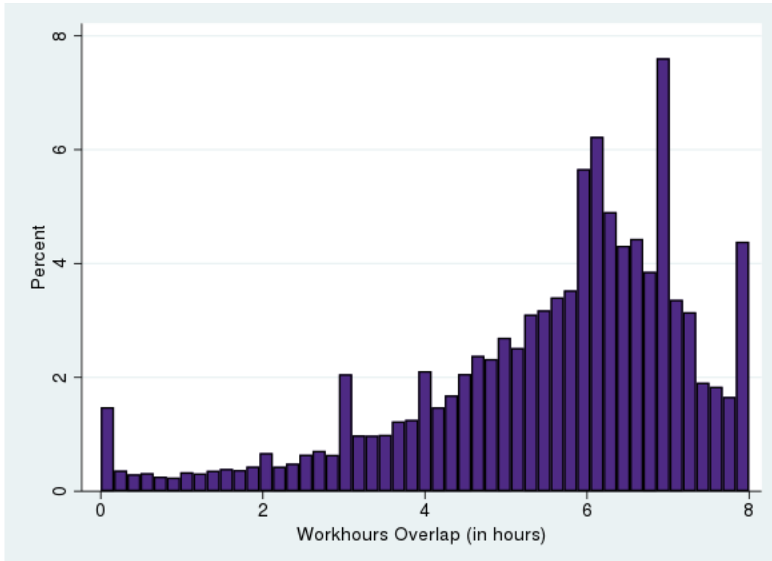

Figure 10: Distribution of Workhours Overlap for Municipality-Activity Pairs (2011-2018)

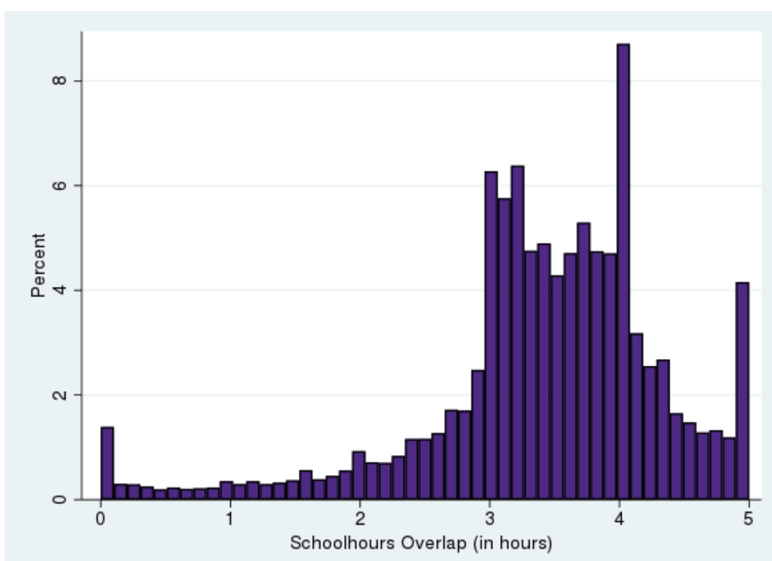

Figure 11: Distribution of Schoolhours Overlap for Municipality-Activity Pairs (2011-2018)

B Preliminary Stylized Facts: Additional Graphs

B.1 By granular impex status (2011)

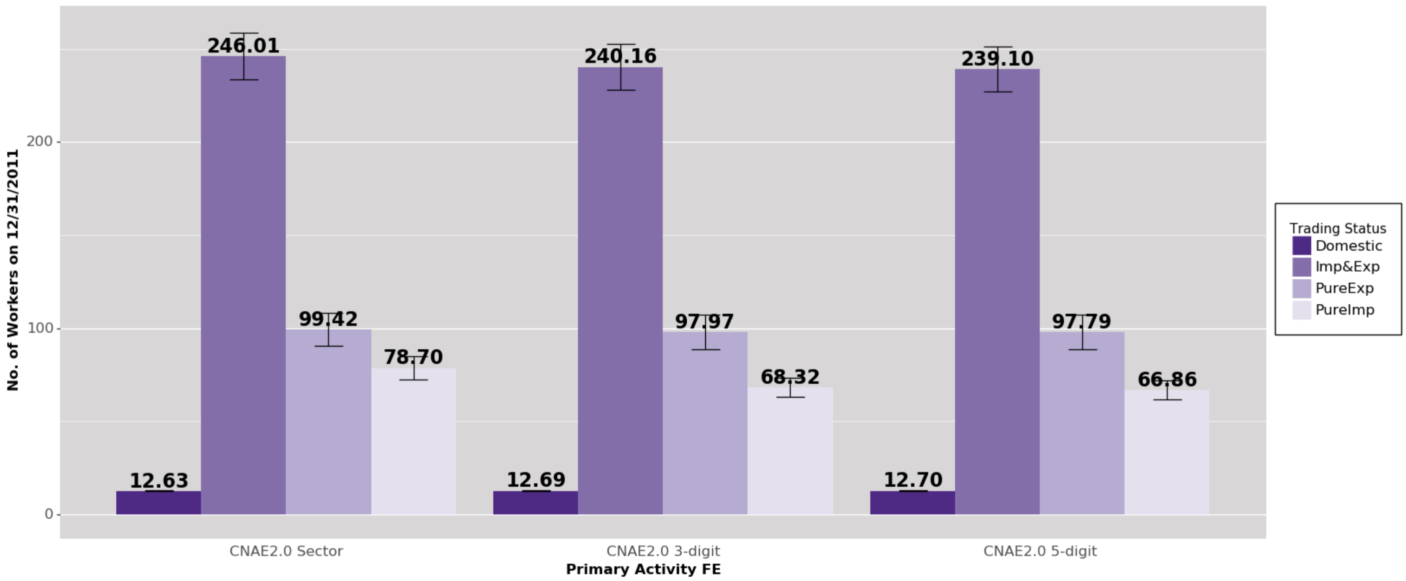

Figure 12: Impex Establishments Employ More Workers (2011)

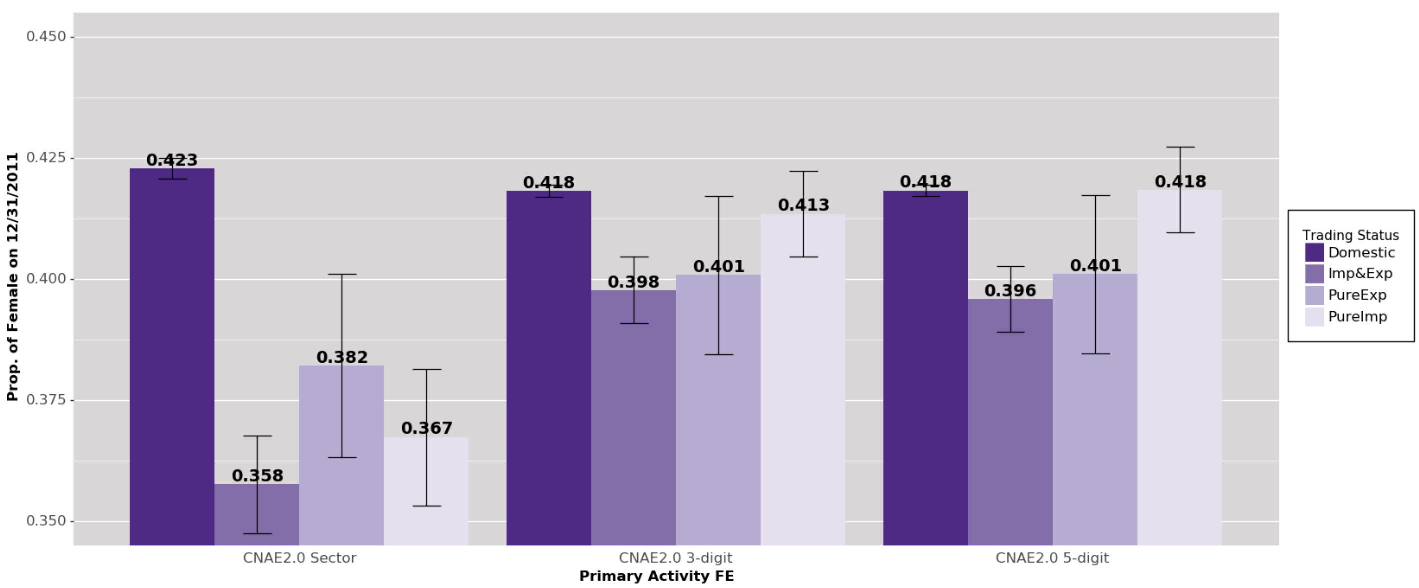

Figure 13: Impex Establishments Employ Proportionally Fewer Women (2011)

Figure 14: The Gender Wage Gap is Higher in Impex Establishments (2011)

B.2 Figures for 2016

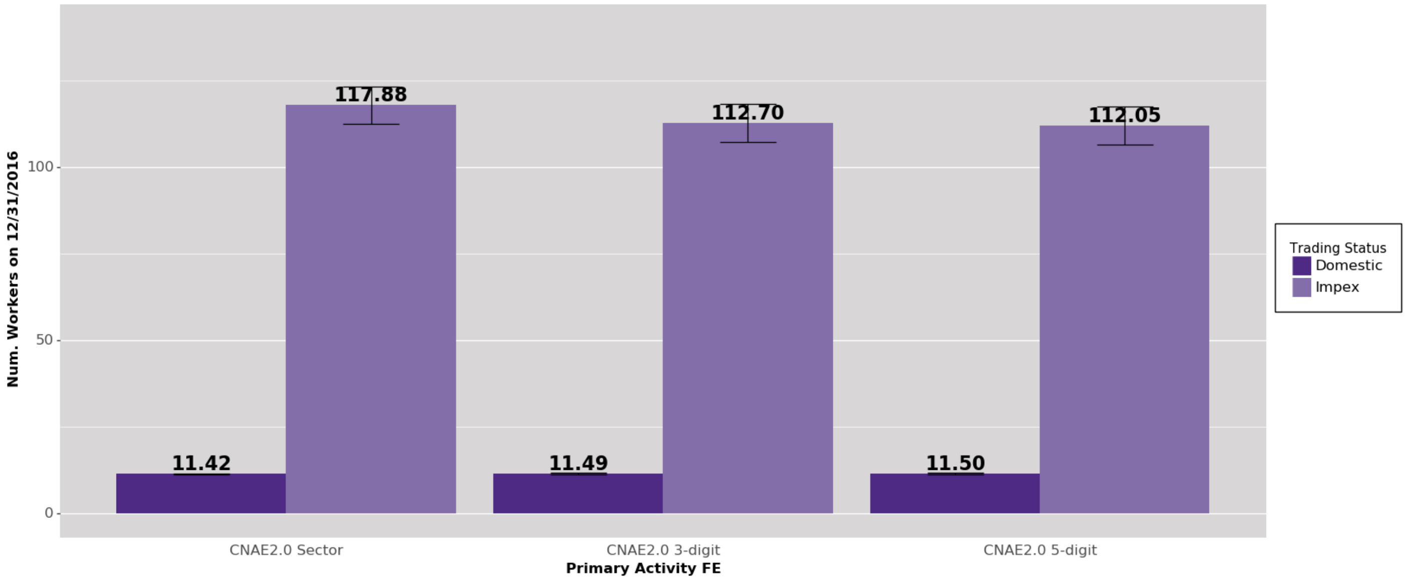

Figure 15: Impex Establishments Employ More Workers (2016)

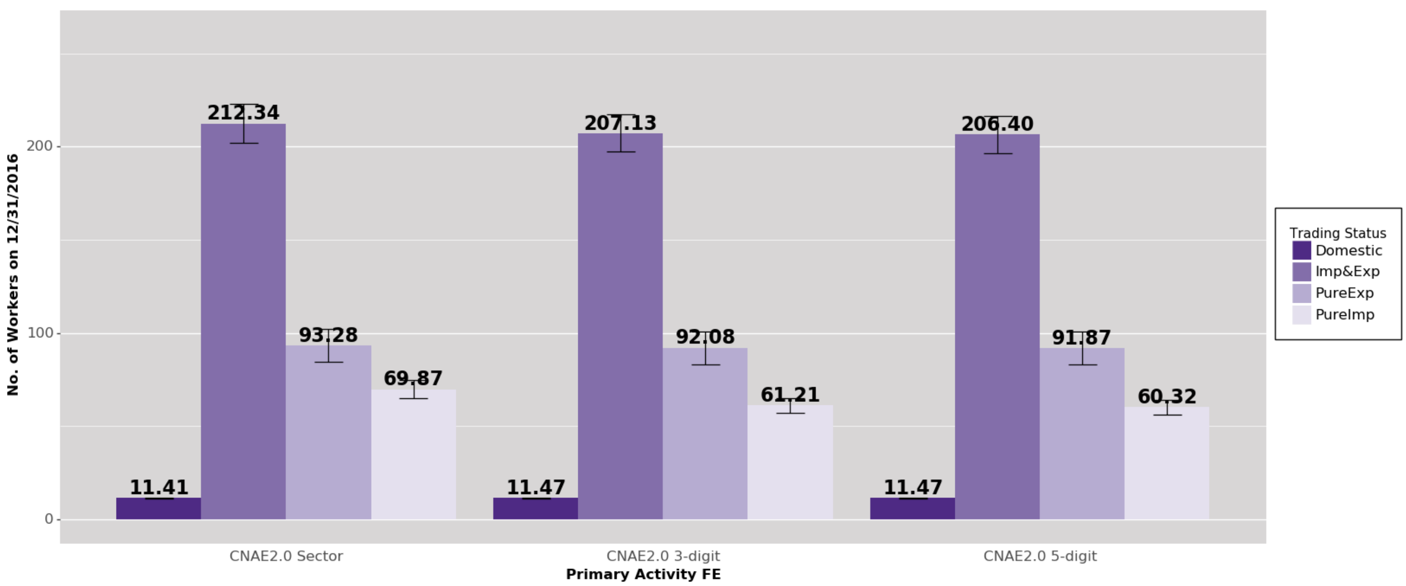

Figure 16: Impex Establishments Employ More Workers (2016)

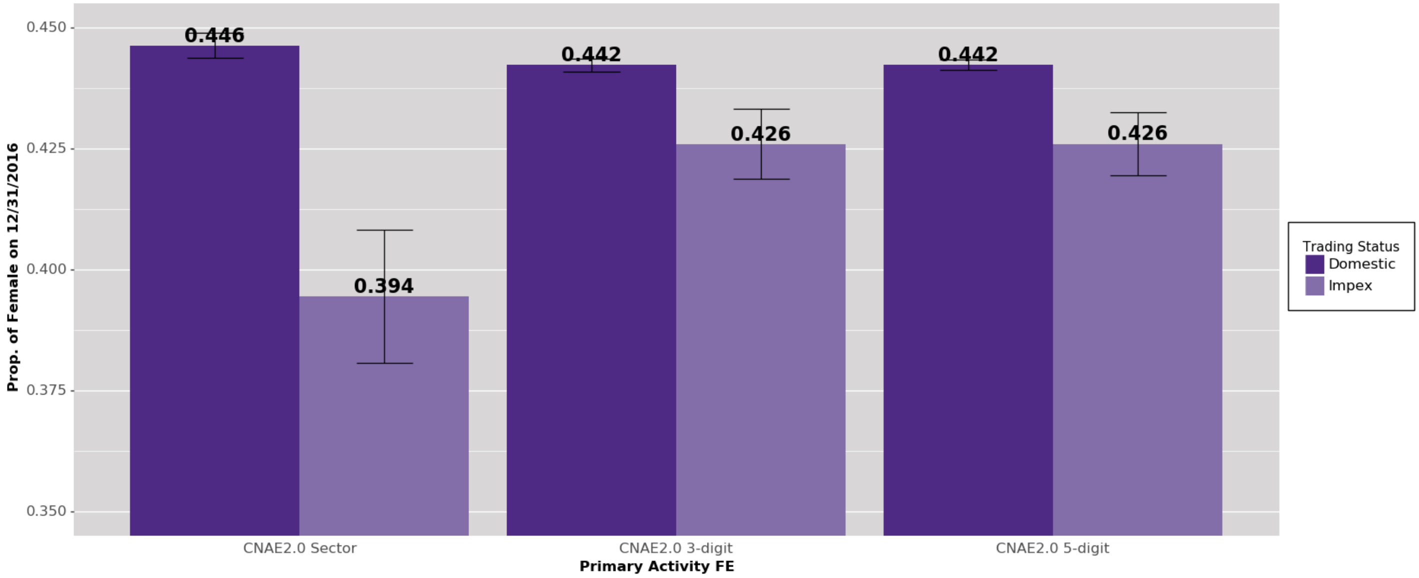

Figure 17: Impex Establishments Employ Proportionally Fewer Women (2016)

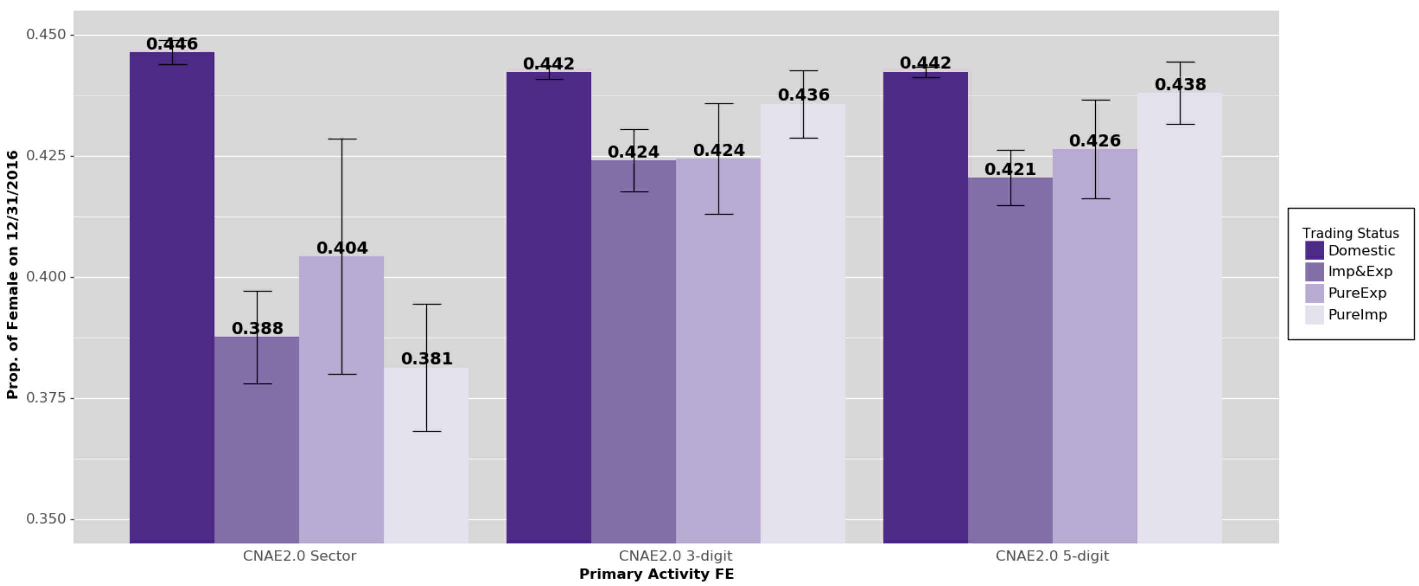

Figure 18: Impex Establishments Employ Proportionally Fewer Women (2016)

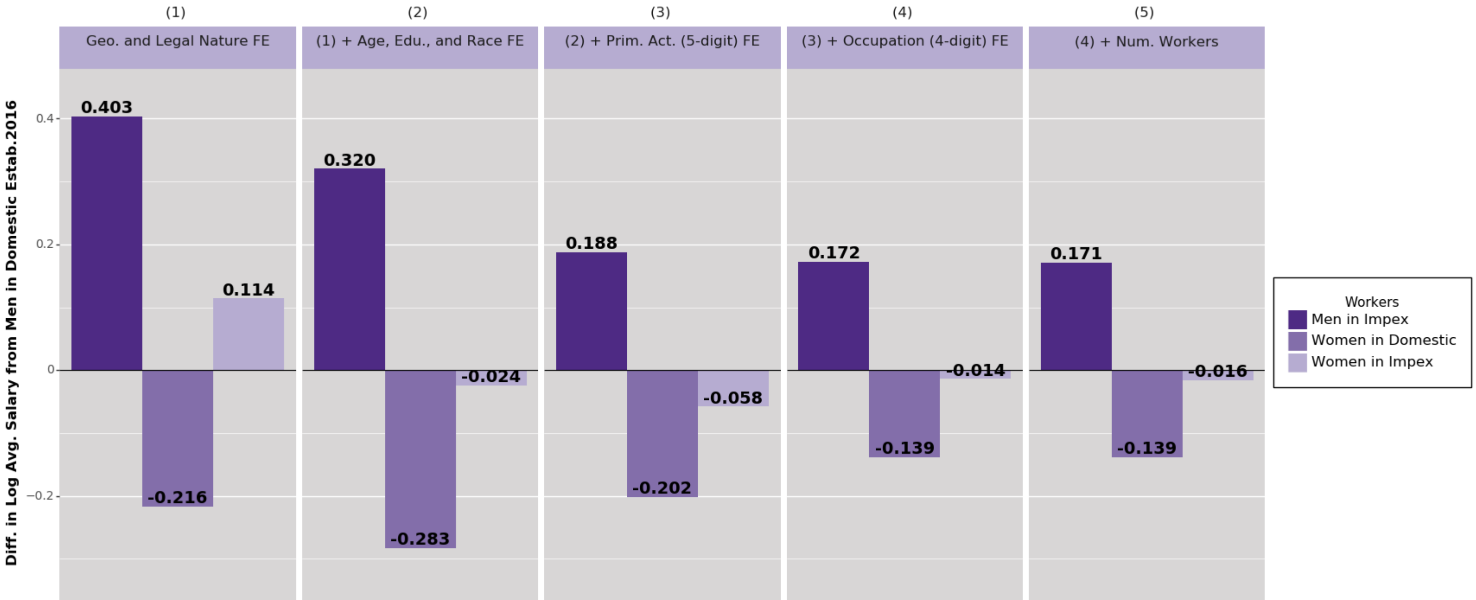

Figure 19: Impex Establishments Pay More (2016)

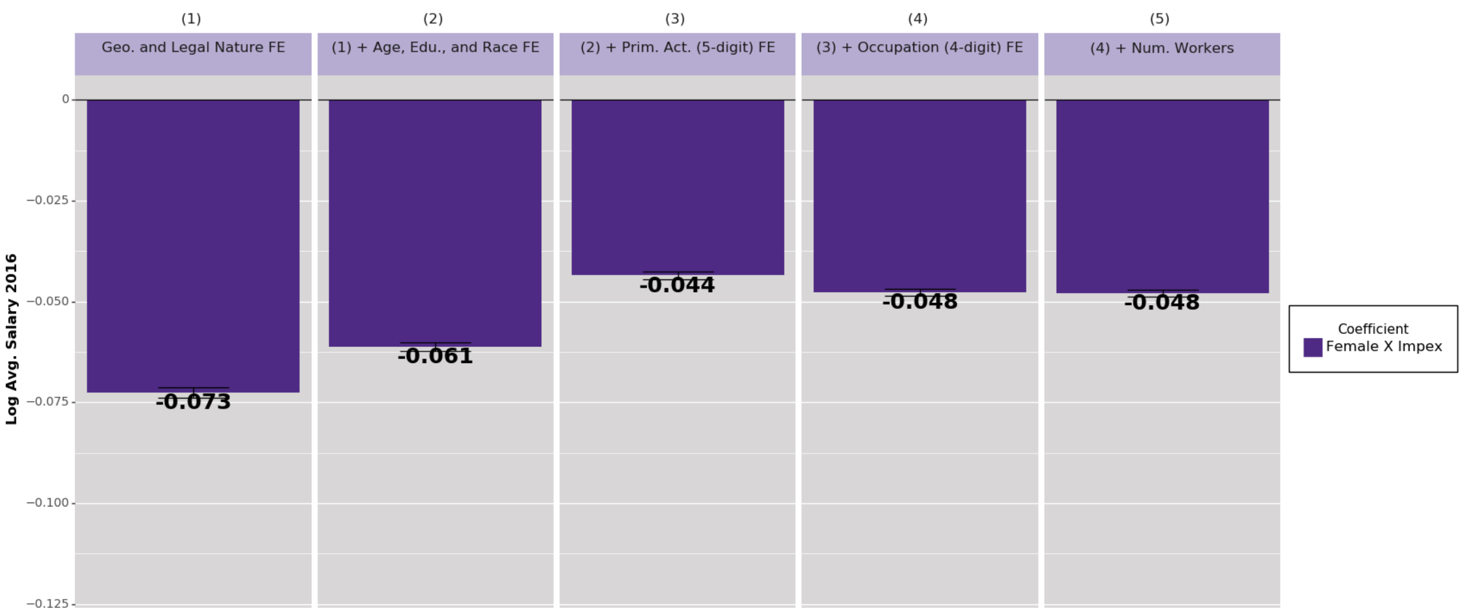

Figure 20: The Gender Wage Gap is Higher in Impex Establishments (2016)

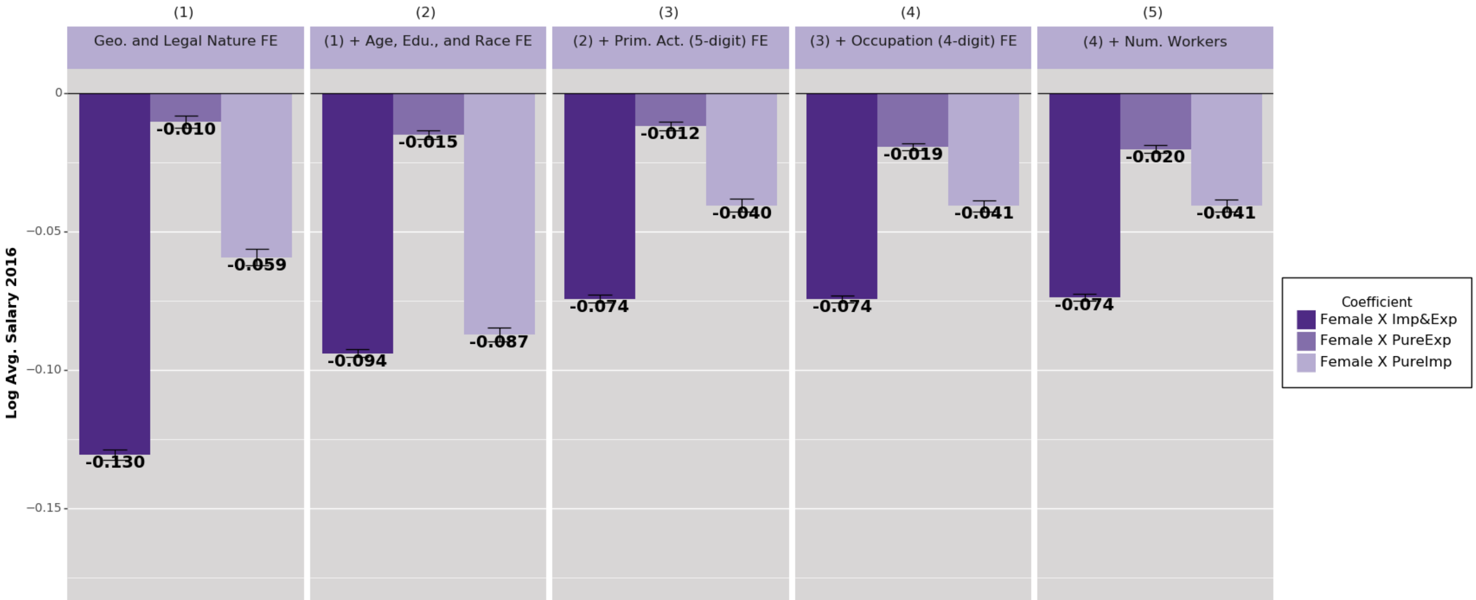

Figure 21: The Gender Wage Gap is Higher in Impex Establishments (2016)

C Additional Robustness Exercises

C.1 Blocked Sample

For the worker-level regressions, I create a new sample to get more precise estimates by excluding workers at domestic establishments who do not have a corresponding counterpart in exporting firms according to:

- their 6-digit occupation code
- the establishments' 5-digit primary activity code
- their municipality
- the establishments' 4-digit legal nature code

This leaves me with around 35 million observations in 2018, with around 14% of them employed in impex establishments. I obtain similar estimates for the outcomes of interest.

C.2 Placebo Regressions: Race instead of Gender

I run the regression equation 3 with the proportion of Black and Mixed Race workers as the dependent variable (instead of the proportion of female workers), and run 4 with an indicator for Black or Mixed Race replacing the indicator for female workers wherever it occurs on the right-hand side. In these regressions, I do not see temporal distance having the same effect as in the corresponding regressions with respect to gender.

C.3 Relevant Workers

Instead of partitioning workers into blue collar workers, white collar workers, and managers, using the 3-digit occupation codes I classify those workers who might be most affected by abnormal workhours induced by foreign clients as 'relevant', and run the previous exercises on this sub-sample. These are positions which I expect have the greatest need for synchronous communication with their clients and management of these interactions. They include some positions in upper management and business administration, sales and service supervisors, medium-level employees involved in commerce, coordinators, etc.[42] Then, the proportion of relevant workers who are female is calculated for every establishment, and fixed effect regressions examining the effect of trading partners on these are run (using the analog of equation 8.) The results are presented in table 16.

Two out of the four measures have statistically and economically significant coefficients: time difference and schoolhours overlap. Over all the regressions, schoolhours overlap has been the most consistently impact. A 3 hour extra overlap leads to 1.5 pp more women employed in exporting firms. The effect on the log of average monthly earnings is reported in table 17. All the interaction terms have coefficients statistically indistinguishable from zero, so in equilibrium, women in 'relevant'

[42] The full list of these occupation codes is in appendix A.1.

Table 16: Firm-Level FE Regressions: Effect on Prop. of Relevant Female Workers

		Robust		Clustered	
Independent Measure	Co-efficient	Std Error	p-value	Std Error	p-value
Longitudinal Distance	-0.00010	0.00015	0.49236	0.00020	0.61000
Time Difference	-0.00265	0.00150	0.07707	0.00229	0.24918
Workhours Overlap	0.00209	0.00174	0.22814	0.00207	0.31342
Schoolhours Overlap	0.00502	0.00201	0.01250	0.00308	0.10405
Observations (degrees of freedom)	85359	(68710)		(283)	

Each line is a separate establishment-level regression with the proportion of female workers as the dependent variable, with establishment and year fixed effects, and conditioned on geodesic distance. Each observation is weighted by the number of workers in the establishment. The clustered standard errors are clustered at the municipio and activity (4-digit) levels.

positions are not differentially affected by further away trading partners. This is not due to the near 90% loss in sample size, the coefficients are all uniformly closer to zero.

Table 17: Worker-level Pooled Regressions: Effect on log(wage) (Relevant Workers, All Exporters)

		Robust		Clustered	
Independent Measure	Co-efficient	Std Error	p-value	Std Error	p-value
Female	-0.2002	0.0098	0.0000	0.0009	0.0000
Longitudinal Distance	-0.0002	0.0008	0.7904	0.0001	0.0003
Female x Longitudinal Distance	0.0001	0.0002	0.5660	0.0000	0.0000
Female	-0.2010	0.0095	0.0000	0.0009	0.0000
Time Difference	-0.0154	0.0072	0.0338	0.0005	0.0000
Female x Time Difference	0.0017	0.0023	0.4620	0.0003	0.0000
Female	-0.1881	0.0177	0.0000	0.0019	0.0000
Workhours Overlap	0.0225	0.0095	0.0182	0.0006	0.0000
Female x Workhours Overlap	-0.0015	0.0030	0.6145	0.0003	0.0000
Female	-0.1883	0.0173	0.0000	0.0021	0.0000
Schoolhours Overlap	0.0046	0.0105	0.6601	0.0008	0.0000
Female x Schoolhours Overlap	-0.0024	0.0047	0.6182	0.0006	0.0001
Observations (deg. of freedom)	2,736,062	(2,735,722)		(287)	

Each section is a separate worker-level regression, conditioned on geodesic distance and tenure, and with age, race, education, contract type, 3-digit occupation, intermediate geographic region, 2-digit activity, and legal nature fixed effects. The clustered standard errors are clustered at the municipio and activity (4-digit) levels.

D Additional Regression Tables

Table 18: **Effect of Motherhood on Separation**

Variable	Coefficient	95% Lower Conf. Limit	95% Upper Conf. Limit
6 Years before Birth × Close Exporter	−0.000121	−0.000470	0.000228
6 Years before Birth × Far Exporter	0.000520	0.000138	0.000901
5 Years before Birth × Close Exporter	0.000904	0.000582	0.001226
5 Years before Birth × Far Exporter	−0.000382	−0.000741	−0.000023
4 Years before Birth × Close Exporter	0.000198	−0.000104	0.000500
4 Years before Birth × Far Exporter	0.000837	0.000501	0.001173
3 Years before Birth × Close Exporter	0.000032	−0.000243	0.000306
3 Years before Birth × Far Exporter	0.000099	−0.000209	0.000408
2 Years before Birth × Close Exporter	0.000658	0.000417	0.000900
2 Years before Birth × Far Exporter	0.000066	−0.000215	0.000347
1 Year before Birth × Close Exporter	−0.000391	−0.000598	−0.000183
1 Year before Birth × Far Exporter	0.000039	−0.000213	0.000292
Year of Birth × Close Exporter	0.061406	0.058231	0.064581
Year of Birth × Far Exporter	0.072432	0.068187	0.076677
1 Year after Birth × Close Exporter	0.036601	0.027151	0.046051
1 Year after Birth × Far Exporter	0.039637	0.031052	0.048221
2 Years after Birth × Close Exporter	0.056926	0.052281	0.061571
2 Years after Birth × Far Exporter	0.065874	0.061059	0.070689
3 Years after Birth × Close Exporter	0.047694	0.044729	0.050660
3 Years after Birth × Far Exporter	0.062671	0.058087	0.067255
4 Years after Birth × Close Exporter	0.039887	0.035963	0.043811
4 Years after Birth × Far Exporter	0.059993	0.052690	0.067295
5 Years after Birth × Close Exporter	0.032064	0.027531	0.036597
5 Years after Birth × Far Exporter	0.052829	0.045796	0.059861
6 Years after Birth × Close Exporter	0.028493	0.021993	0.034992
6 Years after Birth × Far Exporter	0.030482	0.023071	0.037892
Observations		24,181,369	
Degrees of Freedom		236	
Worker-related FE		Age, Race, Education	
Establishment-related FE		Imm. Geo. Region, 3-digit Activity	
Job-related FE		Contract Type, 3-digit Occupation	
Other Controls		Firm Size, Tenure, Year FE	

The sample consists of all women at Close Exporters and Far Exporters, all mothers at Domestic jobs, and a 5% sample of women at domestic earning a positive wage. 95% confidence intervals are constructed using standard errors are clustered at the Municipality and 4-digit Activity levels.

Table 19: Firm-Level Fixed Effect Regressions: Effect on Prop. of Female Workers

		Robust		Clustered	
Independent Measure	Co-efficient	Std Error	p-value	Std Error	p-value
Longitudinal Distance	-0.0001	0.0001	0.2024	0.0001	0.5205
Time Difference	-0.0002	0.0006	0.6845	0.0010	0.8049
Workhours Overlap	-0.0005	0.0007	0.4662	0.0011	0.6278
Schoolhours Overlap	0.0013	0.0008	0.0788	0.0013	0.3089
Observations (deg. of freedom)	90968	(73202)		(284)	

Each line is a separate establishment-level regression with the proportion of female workers as the dependent variable, with establishment and year fixed effects, and conditioned on geodesic distance. Each observation is weighted by the number of workers in the establishment. The clustered standard errors are clustered at the municipio and activity (4-digit) levels.

Table 20: Firm-Level FE Regressions: Effect on Prop. of Female Workers (Unique Exporters)

		Robust		Clustered	
Independent Measure	Co-efficient	Std Error	p-value	Std Error	p-value
Longitudinal Distance	0.0000	0.0001	0.7890	0.0001	0.8561
Time Difference	-0.0002	0.0007	0.7838	0.0009	0.8372
Workhours Overlap	-0.0008	0.0008	0.3108	0.0011	0.4373
Schoolhours Overlap	0.0016	0.0009	0.0816	0.0013	0.1959
Observations (deg. of freedom)	35792	(28035)		(282)	

Each line is a separate establishment-level regression with the proportion of female workers as the dependent variable, with establishment and year fixed effects, and conditioned on geodesic distance. Each observation is weighted by the number of workers in the establishment. The clustered standard errors are clustered at the municipio and activity (4-digit) levels.

Table 21: **Effect of Time Measures on log(Contractual Wage)**

Variable	(1)	(2)
Female	−0.10161***	−0.2485***
	(0.00265)	(0.00007)
Time Difference	0.02433	
	(0.50513)	
Female x Time Difference	−0.01059	
	(0.18756)	
White Collar	0.05207	0.00762
	(0.41966)	(0.90187)
White Collar x Female	−0.08302*	0.11354*
	(0.08645)	(0.09242)
White Collar x Time Difference	−0.00426	
	(0.60720)	
White Collar x Female x Time Difference	0.0173*	
	(0.09757)	
Manager	0.01247	0.13909
	(0.87274)	(0.12899)
Manager x Female	−0.164*	−0.01396
	(0.07561)	(0.89884)
Manager x Time Difference	0.01463	
	(0.21732)	
Manager x Female x Time Difference	0.00851	
	(0.62437)	
Schoolhours Overlap		−0.07734*
		(0.09217)
Female x Schoolhours Overlap		0.03455**
		(0.04526)
White Collar x Schoolhours Overlap		0.00851
		(0.62316)
White Collar x Female x Schoolhours Overlap		−0.04224**
		(0.04879)
Manager x Schoolhours Overlap		−0.02356
		(0.43724)
Manager x Female x Schoolhours Overlap		−0.03808
		(0.33983)
Observations	1,856,305	1,856,305
Degrees of Freedom	277	277
Worker-related FE	Age, Race, Education	
Establishment-related FE	Imm. Geo. Region, 3-digit Activity	
Job-related FE	Contract Type, 3-digit Occupation	
Other Controls	Firm Size, Tenure, Geodesic Distance, Year FE	

Each column contains estimates from a separate worker-level pooled regression. The sample consists of all workers at unique exporters earning a positive wage. The terms in parentheses are p-values from standard errors clustered at the Municipality and 4-digit Activity levels. ****** indicate significance at 10%\5%\1% levels, respectively.

Table 22: **Effect of Time Measures on log(Wage Rate)**

Variable	(1)	(2)
Female	−0.0985***	−0.24898***
	(0.00353)	(0.00007)
Time Difference	0.02384	
	(0.50979)	
Female x Time Difference	−0.01093	
	(0.17320)	
White Collar	0.05503	0.00814
	(0.38698)	(0.89798)
White Collar x Female	−0.08382*	0.11277
	(0.08299)	(0.10470)
White Collar x Time Difference	−0.0044	
	(0.59598)	
White Collar x Female x Time Difference	0.01742	
	(0.10111)	
Manager	0.01211	0.14582
	(0.87328)	(0.11290)
Manager x Female	−0.16482*	−0.02097
	(0.07737)	(0.84930)
Manager x Time Difference	0.01548	
	(0.18414)	
Manager x Female x Time Difference	0.00783	
	(0.65359)	
Schoolhours Overlap		−0.07791*
		(0.09405)
Female x Schoolhours Overlap		0.03531**
		(0.04157)
White Collar x Schoolhours Overlap		0.00913
		(0.60581)
White Collar x Female x Schoolhours Overlap		−0.04211*
		(0.05498)
Manager x Schoolhours Overlap		−0.02483
		(0.41160)
Manager x Female x Schoolhours Overlap		−0.0369
		(0.36046)
Observations	1,856,305	1,856,305
Degrees of Freedom	277	277
Worker-related FE	Age, Race, Education	
Establishment-related FE	Imm. Geo. Region, 3-digit Activity	
Job-related FE	Contract Type, 3-digit Occupation	
Other Controls	Firm Size, Tenure, Geodesic Distance, Year FE	

Each column contains estimates from a separate worker-level pooled regression. The sample consists of all workers at unique exporters earning a positive wage. The terms in parentheses are p-values from standard errors clustered at the Municipality and 4-digit Activity levels. ****** indicate significance at 10%\5%\1% levels, respectively.

Table 23: **Effect of Time Measures on log(Contractual Wage)**

Variable	(1)	(2)	(3)	(4)
Female	−0.14906***	−0.14194***	−0.17247***	−0.22106***
	(0.00000)	(0.00000)	(0.00000)	(0.00000)
Longitudinal Distance	−0.0012			
	(0.62436)			
Female x Longitudinal Distance	−0.00012			
	(0.70877)			
Time Difference		0.02415		
		(0.45657)		
Female x Time Difference		−0.00366		
		(0.47971)		
Workhours Overlap			−0.03046	
			(0.47981)	
Female x Workhours Overlap			0.00367	
			(0.58783)	
Schoolhours Overlap				−0.06913*
				(0.09946)
Female x Schoolhours Overlap				0.02119*
				(0.08749)
Observations	1,930,974	1,930,974	1,930,974	1,930,974
Degrees of Freedom	277	277	277	277
Worker-related FE	Age, Race, Education			
Establishment-related FE	Imm. Geo. Region, 3-digit Activity			
Job-related FE	Contract Type, 3-digit Occupation			
Other Controls	Firm Size, Tenure, Geodesic Distance, Year FE			

Each column contains estimates from a separate worker-level pooled regression. The sample consists of all workers at unique exporters earning a positive wage. The terms in parentheses are p-values from standard errors clustered at the Municipality and 4-digit Activity levels. ****** indicate significance at 10%\5%\1% levels, respectively.

Table 24: **Effect of Time Measures on log(Wage Rate)**

Variable	(1)	(2)	(3)	(4)
Female	−0.14642***	−0.13914***	−0.1726***	−0.22274***
	(0.00000)	(0.00000)	(0.00000)	(0.00000)
Longitudinal Distance	−0.00137			
	(0.57300)			
Female x Longitudinal Distance	−0.00014			
	(0.65731)			
Time Difference		0.02355		
		(0.46403)		
Female x Time Difference		−0.00401		
		(0.43426)		
Workhours Overlap			−0.02944	
			(0.48735)	
Female x Workhours Overlap			0.00402	
			(0.54632)	
Schoolhours Overlap				−0.06945
				(0.10227)
Female x Schoolhours Overlap				0.02221*
				(0.07339)
Observations	1,930,974	1,930,974	1,930,974	1,930,974
Degrees of Freedom	277	277	277	277
Worker-related FE	Age, Race, Education			
Establishment-related FE	Imm. Geo. Region, 3-digit Activity			
Job-related FE	Contract Type, 3-digit Occupation			
Other Controls	Firm Size, Tenure, Geodesic Distance, Year FE			

Each column contains estimates from a separate worker-level pooled regression. The sample consists of all workers at unique exporters earning a positive wage. The terms in parentheses are p-values from standard errors clustered at the Municipality and 4-digit Activity levels. ****** indicate significance at 10%\5%\1% levels, respectively.

Table 25: **Effect of Time Measures on Hours**

Variable	(1)	(2)	(3)	(4)
Female	−0.12438***	−0.12388***	0.05196	0.09234
	(0.00004)	(0.00009)	(0.24011)	(0.10709)
Longitudinal Distance	−0.00212			
	(0.11049)			
Female x Longitudinal Distance	0.00127***			
	(0.00632)			
Time Difference		−0.00513		
		(0.69197)		
Female x Time Difference		0.01918***		
		(0.00497)		
Workhours Overlap			0.00167	
			(0.91917)	
Female x Workhours Overlap			−0.02264***	
			(0.00396)	
Schoolhours Overlap				0.01652
				(0.32966)
Female x Schoolhours Overlap				−0.04642***
				(0.00511)
Observations	3,048,645	3,048,645	3,048,645	3,048,645
Degrees of Freedom	280	280	280	280
Worker-related FE	Age, Race, Education			
Establishment-related FE	Imm. Geo. Region, 3-digit Activity			
Job-related FE	Contract Type, 3-digit Occupation			
Other Controls	Firm Size, Tenure, Geodesic Distance, Year FE			

Each column contains estimates from a separate worker-level pooled regression. The sample consists of all workers at unique exporters earning a positive wage. The terms in parentheses are p-values from standard errors clustered at the Municipality and 4-digit Activity levels. ****** indicate significance at 10%\5%\1% levels, respectively.

Table 26: **Effect of Time Measures on Prop. of White Collar Workers who are Female**

Variable	(1)	(2)	(3)	(4)
Longitudinal Distance	−0.00099**			
	(0.01992)			
Time Difference		−0.0075**		
		(0.03946)		
Workhours Overlap			0.00274	
			(0.54527)	
Schoolhours Overlap				0.01311**
				(0.03224)
Weighted Observations	512,115	512,115	512,115	512,115
Degrees of Freedom	279	279	279	279
Establishment-related FE	Imm. Geo. Region, 3-digit Activity			
Other Controls	Firm Size, Geodesic Distance, Year FE			

Each column contains estimates from a separate establishment-level pooled regression. The sample consists of establishments which are unique exporters with at least 1 white collar worker. The terms in parentheses are p-values from standard errors clustered at the Municipality and 4-digit Activity levels. ****** indicate significance at 10%\5%\1% levels, respectively.

Table 27: **Effect of Time Measures on Prop. of Blue Collar Workers who are Female**

Variable	(1)	(2)	(3)	(4)
Longitudinal Distance	−0.00073*			
	(0.08444)			
Time Difference		−0.00089		
		(0.78528)		
Workhours Overlap			0.00193	
			(0.59257)	
Schoolhours Overlap				0.00287
				(0.58175)
Weighted Observations	2,212,998	2,212,998	2,212,998	2,212,998
Degrees of Freedom	275	275	275	275
Establishment-related FE	Imm. Geo. Region, 3-digit Activity			
Other Controls	Firm Size, Geodesic Distance, Year FE			

Each column contains estimates from a separate establishment-level pooled regression. The sample consists of establishments which are unique exporters with at least 1 blue collar worker. The terms in parentheses are p-values from standard errors clustered at the Municipality and 4-digit Activity levels. ****** indicate significance at 10%\5%\1% levels, respectively.

Table 28: **Effect of Time Measures on Prop. of Managers who are Female**

Variable	(1)	(2)	(3)	(4)
Longitudinal Distance	−0.00015			
	(0.76197)			
Time Difference		0.00058		
		(0.86747)		
Workhours Overlap			0.00187	
			(0.67119)	
Schoolhours Overlap				0.00315
				(0.51020)
Weighted Observations	93,386	93,386	93,386	93,386
Degrees of Freedom	270	270	270	270
Establishment-related FE	Imm. Geo. Region, 3-digit Activity			
Other Controls	Firm Size, Geodesic Distance, Year FE			

Each column contains estimates from a separate establishment-level pooled regression. The sample consists of establishments which are unique exporters with at least 1 manager. The terms in parentheses are p-values from standard errors clustered at the Municipality and 4-digit Activity levels. ****** indicate significance at 10%\5%\1% levels, respectively.

Table 29: **Effect of Time Measures on Leaves**

Variable	(1)	(2)	(3)	(4)
Female	5.31183***	5.32938***	5.7725***	5.48075***
	(0.00000)	(0.00000)	(0.00000)	(0.00000)
Longitudinal Distance	−0.00395			
	(0.55065)			
Female x Longitudinal Distance	0.00251			
	(0.52071)			
Time Difference		−0.0329		
		(0.60382)		
Female x Time Difference		0.03313		
		(0.57813)		
Workhours Overlap			0.13321	
			(0.53665)	
Female x Workhours Overlap			−0.06744	
			(0.42179)	
Schoolhours Overlap				−0.30908***
				(0.00923)
Female x Schoolhours Overlap				−0.01065
				(0.92246)
Observations	5,151,082	5,151,082	5,151,082	5,151,082
Degrees of Freedom	283	283	283	283
Worker-related FE	Age, Race, Education			
Establishment-related FE	Imm. Geo. Region, 3-digit Activity			
Job-related FE	Contract Type, 3-digit Occupation			
Other Controls	Firm Size, Tenure, Geodesic Distance, Year FE			

Each column contains estimates from a separate worker-level pooled regression. The sample consists of all workers at all exporters earning a positive wage. The terms in parentheses are p-values from standard errors clustered at the Municipality and 4-digit Activity levels. ****** indicate significance at 10%\5%\1% levels, respectively.

Table 30: **Effect of Time Measures on Leaves**

Variable	(1)	(2)	(3)	(4)
Female	5.83241***	5.89618***	6.01604***	5.88039***
	(0.00000)	(0.00000)	(0.00000)	(0.00000)
Longitudinal Distance	0.00499			
	(0.51623)			
Female x Longitudinal Distance	0.00185			
	(0.58171)			
Time Difference		−0.02849		
		(0.59733)		
Female x Time Difference		0.01085		
		(0.83270)		
Workhours Overlap			0.34785**	
			(0.04842)	
Female x Workhours Overlap			−0.01748	
			(0.78496)	
Schoolhours Overlap				−0.2886***
				(0.00235)
Female x Schoolhours Overlap				0.01969
				(0.84629)
Observations	3,048,645	3,048,645	3,048,645	3,048,645
Degrees of Freedom	280	280	280	280
Worker-related FE	Age, Race, Education			
Establishment-related FE	Imm. Geo. Region, 3-digit Activity			
Job-related FE	Contract Type, 3-digit Occupation			
Other Controls	Firm Size, Tenure, Geodesic Distance, Year FE			

Each column contains estimates from a separate worker-level pooled regression. The sample consists of all workers at unique exporters earning a positive wage. The terms in parentheses are p-values from standard errors clustered at the Municipality and 4-digit Activity levels. ****** indicate significance at 10%\5%\1% levels, respectively.

Table 31: **Effect of Time Measures on Hours**

Variable	(1)	(2)
Female	−0.13016***	0.05595
	(0.00291)	(0.39590)
Time Difference	−0.01113	
	(0.36597)	
Female x Time Difference	0.01916**	
	(0.03533)	
White Collar	−0.08904	0.01407
	(0.19581)	(0.88066)
White Collar x Female	0.02395	0.06197
	(0.69541)	(0.59818)
White Collar x Time Difference	0.0107	
	(0.32520)	
White Collar x Female x Time Difference	−0.00342	
	(0.83460)	
Manager	−0.09405	−0.07408
	(0.39167)	(0.30979)
Manager x Female	−0.01199	0.08428
	(0.89126)	(0.49702)
Manager x Time Difference	0.00284	
	(0.76574)	
Manager x Female x Time Difference	0.00575	
	(0.72883)	
Schoolhours Overlap		0.02481
		(0.16922)
Female x Schoolhours Overlap		−0.03659*
		(0.06144)
White Collar x Schoolhours Overlap		−0.01985
		(0.39349)
White Collar x Female x Schoolhours Overlap		−0.01725
		(0.60606)
Manager x Schoolhours Overlap		−0.00236
		(0.89891)
Manager x Female x Schoolhours Overlap		−0.02526
		(0.53499)
Observations	2,938,803	2,938,803
Degrees of Freedom	280	280
Worker-related FE	Age, Race, Education	
Establishment-related FE	Imm. Geo. Region, 3-digit Activity	
Job-related FE	Contract Type, 3-digit Occupation	
Other Controls	Firm Size, Tenure, Geodesic Distance, Year FE	

Each column contains estimates from a separate worker-level pooled regression. The sample consists of all workers at unique exporters earning a positive wage. The terms in parentheses are p-values from standard errors clustered at the Municipality and 4-digit Activity levels. ****** indicate significance at 10%\5%\1% levels, respectively.